Shocks and spillovers in the global environment

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by

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Contents

[1]This chapter has been published as Miescu, M.S., 2018. Together in bad times? Connectedness and spillovers in recession and boom. The Manchester School.

[2]This chapter is coauthored with Ursel Baumann and David Lodge, ECB. The paper is available in the ECB working papers series as: Baumann, U., Lodge, D. and Miescu, M.S., 2019. Global growth on life support? The contributions of fiscal and monetary policy since the global financial crisis (No. 2248).

[3]The content of this chapter should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB.

Declaration

I, Mirela Sorina Miescu, confirm that the research included within this thesis is my own work or that where it has been carried out in collaboration with, or supported by others, that this is duly acknowledged below and my contribution indicated. Previously published material is also acknowledged below.

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Abstract

The thesis explores different aspects of shocks transmission and spillovers in a global environment. Chapter 1 assesses the effect of participation of countries in IMF programs on their vulnerability to external shocks. The analysis uses vector autoregressive models (hereafter VAR) to construct a proxy for the exposure to external shocks. The article then examines how this impact depends on the participation of a country in IMF programs and finds that a higher rate of participation in IMF arrangements is associated with a smaller vulnerability to external shocks.

Chapter 2 focuses on the variation of connectedness among countries with the state of the economy. The connectedness of real output, inflation and financial variables for seven advanced economies is measured via a Bayesian Threshold VAR model. It is reported that the global connectedness is sizable and business cycle dependent, with higher values during recessions.

Chapter 3 quantifies the role of monetary and fiscal shocks in advanced and emerging economies using a panel VAR with hierarchical structure. The policy contribution on GDP growth is assessed by means of a structural counterfactual analysis based on conditional forecasts. Results show that global GDP growth benefited from substantial policy support during the global financial crisis but policy tightening thereafter, particularly fiscal consolidation, acted as a significant drag on subsequent global recovery.

The final chapter investigates the effects of domestic uncertainty shocks in emerging economies. A new Bayesian algorithm is developed to estimate proxy panel VAR models with hierarchical structure. To identify exogenous uncertainty shocks in the fifteen EMEs, fluctuations in global uncertainty are used as a proxy for domestic uncertainty shocks. The main findings suggest that uncertainty shocks cause severe falls in GDP and stock price indexes, have inflationary effects, depreciate the currency and are not followed by a subsequent overshoot in activity.

The replication files for the four chapters of the thesis are available at the following public link: https://www.dropbox.com/sh/3psfj4qhabp3ooz/AAAxgeKADbeaRExI332iWDN1a?dl=0

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Introduction

This thesis investigates the transmission of economic shocks within and between countries from an empirical perspective. Specifically, evidence is presented on issues related to the international dimension of the business cycle, which have recently gained considerable attention from both policymakers and academic research. These include questions about the role of IMF programs on the external exposure of a country, the variation of a cross-country spillover index across business cycle phases, the contribution of monetary and fiscal policy to the GDP growth in advanced and emerging economies and the effects of uncertainty shocks in a group of emerging countries.

The methodology employed relies on structural VAR models, which have become a key econometric tool to asses the effects of shocks from an empirical perspective. To estimate the models, in this work a Bayesian approach is preferred for its flexibility in dealing with non-linearity and hierarchical models while addressing the "curse of dimensionality".

There are four main research themes in this thesis which are organized in four distinct chapters as follows:

IMF programs and sensitivity to external shocks

The role of IMF program participation and the sensitivity of countries to external shocks will be discussed in Chapter 1. Currently, one of the primary purposes of the IMF is to ensure global stability. As such, the Fund has the responsibility of advising member countries on the financial and economic policies that promote stability, helping to avoid crises and smoothing the adjustment to exogenous shocks. Applying a bilateral Structural VAR model to a panel of 165 countries, the analysis isolates a set of external shocks, estimates their impact on the economy of each country in the sample and uses this estimate as a proxy for the exposure to external shocks. The article then examines how this impact depends on the participation of a country in IMF programs and finds that a higher rate of participation in IMF arrangements is associated with a smaller vulnerability to external shocks. These results are of considerable interest since shocks and crises are a systematic feature of the global economy which affects both developing and developed countries.

This chapter brings two main contributions to the literature. First, we provide new evidence on the impact of IMF intervention on the vulnerability of countries to non-domestic shocks focusing on almost all countries of the world. Second, taking advantage of the large data-set employed we formally quantify the impact of IMF participation on the external vulnerability of a country in a cross-section analysis.

Connectedness and spillovers in recession and boom

We will investigate the variation across business cycle phases of the connectedness among countries in Chapter 2. Enhanced correlation of GDP growth rates across countries during the global financial crisis has spurred renewed interest of policymakers and academics in the international business cycle and the cross-country co-movements in economic activity. The literature supports the evidence of commonality in macroeconomic fluctuations across countries, particularly for advanced economies (Kose et al., 2003; Canova et al., 2007; Diebold and Yilmaz, 2013; Antonakakis et al., 2016) as well as the idea that the business cycle is asymmetric, with recessions and expansions characterized by swings of different magnitude (see Neftci, 1984; Morley and Piger, 2012;Vavra 2013; Bloom, 2014). On these grounds, in this chapter we investigate the state dependency of the connectedness across countries. To this purpose, we apply the Diebold-Yilmaz index in a non-linear framework. Via a Threshold VAR model, we measure the connectedness in recessions and booms of industrial production, inflation and financial variables for seven advanced economies. The global connectedness is shown to be sizable and business cycle dependent. Specifically, the results suggest that higher values are recorded during recessions. Financial and nominal connectedness display different dynamics relative to the connectedness in industrial production. In addition, while Europe appears to be vulnerable to shocks originated in USA and Japan, the US is unaffected by shocks occurring elsewhere. Results are robust to an alternative state-dependent modelling of the parameters and our model fit outperforms both the linear VAR and the Smooth Transition VAR.

The contribution of this chapter to the literature is threefold. First, we investigate the regime-dependency of macroeconomic connectedness of seven industrialized countries. Second, the empirical setting employed captures the sign asymmetry of shocks as well, and we show that negative innovations increase connectedness more than the positive ones. Finally, we extend the benchmark model featuring IP as real activity variable to also include financial and nominal ones. As such, we provide novel evidence on the composition of the global connectedness index and its variation over the business cycle.

The contributions of fiscal and monetary policy since the global financial crisis

We will provide evidence on the role of monetary and fiscal policy on GDP growth in advanced and emerging economies in Chapter 3. Strong policy support was necessary to reignite the economic recovery from the 2008 global financial crisis. In part reflecting different economic conditions and challenges, the policy response across advanced and emerging market economies (EMEs) was somewhat heterogeneous. Up to now, very little attention has been paid to analyzing the differences (or similarities) in the role played by policy support in advanced economies and EMEs. A deeper understanding of how policy contributed across both groups of countries would benefit to both policymakers and academics. To this end, we use a model with a hierarchical structure to capture the variability of GDP response to policy shocks both between and within the groups of advanced and emerging countries. We provide evidence that fiscal policy effects are heterogeneous across countries, with higher multipliers in advanced economies compared to emerging markets, while monetary policy is found to have more homogeneous effects on GDP. We then quantify the policy contribution on GDP growth in the last decade by means of a structural counterfactual analysis based on conditional forecasts. We find that global GDP growth benefited from substantial policy support during the global financial crisis but policy tightening thereafter, particularly fiscal consolidation, acted as a significant drag on the subsequent global recovery. In addition we show that the role of policy has differed across countries. Specifically, in advanced economies, highly accommodative monetary policy has been counteracted by strong fiscal consolidation. By contrast, in emerging economies, monetary policy has been less accommodative since the global recession.

While a vast literature has focused on the effects of either monetary or fiscal policy on individual countries, we evaluate and compare the effects of policy across a range of advanced and emerging market economies, and we look at the effects of fiscal and monetary policy in combination. To discern the effect of fiscal and monetary policy on GDP growth we use counterfactual scenarios in the spirit of Lenza et al. (2010) and Kapetanios et al. (2012) but we differ by relying on the structural form of the model, attributing outcomes for policy specifically to the relevant monetary and fiscal shocks identified in our model. Moreover, we study the interaction and interdependency of the two branches of macroeconomic policy over the past decade by asking questions such as: how might monetary policy have behaved if fiscal policy had been conducted differently?; and how strong would fiscal support have needed to be, had monetary policy been less accommodative?

Uncertainty shocks in emerging economies

Chapter 4 analyses the effects of domestic uncertainty shocks in emerging economies. Following the 2008 global financial crisis an extensive literature focused on the concept of uncertainty and its role in driving the business cycle. Although there is no single theory describing the effects of uncertainty, substantial evidence associates higher uncertainty with recessions. Despite the fact that extensive research has been carried out on the topic of uncertainty, little is known about the effects of uncertainty shocks in emerging economies. This lack of evidence can be largely attributed to the limited availability and accuracy of data for these countries. In this chapter we propose a new Bayesian algorithm to estimate proxy panel structural vector autoregressive models with hierarchical structure. We then construct a global uncertainty indicator as well as country uncertainty measures for fifteen relatively small emerging economies. To identify exogenous uncertainty shocks in the fifteen EMEs we use fluctuations in global uncertainty as a proxy for domestic uncertainty shocks. We find that uncertainty shocks cause severe falls in GDP and stock price indexes, depreciate the currency and are not followed by a subsequent overshoot in activity. Moreover, our results are consistent with a "supply side" type uncertainty shock generating an increase in consumer prices and an ambiguous reaction of the monetary policy. Finally, we show that there is heterogeneity across economies in the response to uncertainty shocks which can be (in part) explained by country characteristics.

This chapter makes three important contributions. To begin with, to the best of our knowledge, this is the first paper that investigates the effects of domestic uncertainty shocks in emerging economies, while accounting for the potential co-movement between uncertainty and the real activity. Second, from a methodological point of view we develop a novel Bayesian algorithm to estimate an extended version of a panel VAR with random coefficients. Finally, from an economic perspective, we propose the use of global uncertainty fluctuations as an instrument for domestic uncertainty shocks.

Chapter 1

IMF programs and sensitivity to external shocks

1.1 Introduction

The last two decades have seen a profound acceleration of international transactions. The collapse of the Berlin Wall and the increased salience of global capital flows pushed the IMF to undertake much wider and weighty interventions in global domestic politics. Today the Fund is one of the most important international organization in the global system and it exerts greater influence than practically any other international organization in history. Until recently, around four out of five members of the Fund have used its resources at least once.

As specified in the IMF official site, one of the main purposes of the Fund‘s lending activity is to insure global stability helping member countries to prevent crisis and to smooth the adjustment to various shocks. In a world where shocks and crises have increased their frequency, the need for countries to protect themselves from external shocks has become more urgent. As such, addressing the external exposure of countries has turned into one of the main aspects of the IMF‘s agenda.

Although researchers have shown a growing interest in analyzing the role of IMF lending on the financial stability of member countries (Kireyev 2010, Dreher and Walter 2010, Papi et al. 2016), very little is known about the Fund‘s efficiency in helping countries to protect themselves against non-domestic shocks. A likely explanation for this lack of evidence is that there are no well established measures for the sensitivity of a country to external shocks. The purpose of this paper is to address this research gap evaluating the impact of IMF programs on the sensitivity of a country to non-domestic shocks. The methodology employed builds on Canova (2005) and Loayza and Raddatz (2007) who apply vector autoregressions to isolate external shocks, estimate their impact on domestic variables and use it as a measure for the external vulnerability. Following their approach we construct an unbalanced panel of 165 countries ranging from 10 to 55 years of quarterly observations. A bilateral VAR consisting of a domestic and an external block is estimated for each country and the average effect of external shocks on the domestic economy is used as a proxy for the external exposure. The impact of IMF programs on the external exposure of countries is then examined in a cross section analysis. The endogeneity issue is addressed by instrumenting the participation in the IMF loans with the size of the IMF quota in the spirit of Barro and Lee (2005).

The main finding of the paper is that IMF program participation decreases the sensitivity of borrowing countries to non-domestic shocks. A number of robustness checks reinforce the validity of the empirical results.

Our paper brings several contributions to the literature. First, to the best of our knowledge, Kireyev (2000) is the only study that has analyzed the impact of IMF intervention on the vulnerability of countries to non-domestic shocks. However, he restricts his attention to 18 Arabic countries while we include in our sample almost all countries of the world. Second, we adopt a different empirical approach. Instead of a Panel VAR model with Cholesky decomposition, we estimate a Bayesian VAR (hereafter BVAR) model with shocks identified through sign restrictions. The Bayesian methods deal in a more efficient way with the high heterogeneity in the data quality and availability, hence are an attractive choice for the purposes of this article. In addition, we use the outcome of the BVAR analysis to build a proxy for the external exposure. Finally, taking advantage of the large data-set employed we take a further step in our study and we formally quantify the impact of IMF participation on the external vulnerability of a country in a cross-section analysis.

There are several channels through which IMF arrangements can help a country improve its capacity of absorbing the external shocks. One good example is the IMF program itself which consists of a given amount of financing and a set of economic policy adjustments (i.e. "conditionality") that the borrower must implement. The money should alleviate restructuring the economy (even if not always verified in practice) and boost the reserves, thus reducing the likelihood of currency speculative attacks (Dreher and Walter 2010). The conditions to be implemented and the policy advice that IMF staff provides to the borrower should reinforce the economic resilience and decrease the risk of external shocks. In addition, the presence of an IMF program acts as a "seal of approval" that the country is undertaking measures to address the macroeconomic imbalances; this fact should restore the investor's confidence and decrease the risk of currency attacks. On the other side, IMF lending could also induce moral hazard since the loan acts as an income insurance against adverse shocks. The insurance cover could incentivize the borrowing countries to lower the precautions to such shocks deepening the economic and financial fragility (Vaubel 1983). Even if there are strong reasons to believe that IMF programs should impact on the external exposure of a country, the theoretical arguments do not provide a clear answer on the sign of this effect. This article attempts to shed some light in this direction.

The structure of the paper is as follows. Section 2 presents a brief review of the existing literature. Section 3 and 4 introduce the methodology and the data. In section 5 we use the results derived from the BVAR analysis to construct an index of external vulnerability. In section 6 we use this measure in a cross section analysis where we investigate the effect of participation in IMF programs on the member sensitivity‘s to non-domestic shocks. Robustness checks to the model heterogeneity, the identification strategy and the choice of external variables are available in the appendix.

1.2 Related literature

Kireyev (2000) employs a Panel VAR to examine the effect of external and domestic shocks on macroeconomic dynamics of the Arabic countries. He then compares the impact of these shocks on countries while under IMF program and not. He finds that on average, countries are less vulnerable to adverse exogenous shocks while under IMF program.

Building on Kireyev (2000) and the previous literature, we propose a BVAR model in the spirit of Canova (2005) and we test the difference in the sensitivity to exogenous shocks for countries under IMF arrangement and not. We then check the statistical significance of our results in a cross-section analysis.

Our paper brings contributions to two broad strands of the literature. In particular, we add to the studies that evaluate the effects of IMF programs. As suggested by Haque and Khan (1998), an important question often raised in relation to the Fund programs is whether such programs are efficient in terms of improving the current account balance, increasing international reserves, lowering inflation, raising the growth rate and mitigating the financial instability. The results of most of the cross-country empirical studies are rather mixed. They point out that IMF programs lead to improvement in the current account balance and the balance of payment but they have a negative impact on output in the short run. Binder and Bluhm (2014) find that positive effects of IMF loans on growth are coupled with progress in institutional quality. Several studies indicate that inflation falls for countries under IMF arrangements, but this result is mainly not statistically significant (Conway 1994, Barro and Lee 2005, Easterley 2005, Dreher 2006). IMF‘s role in catalyzing private capital flows has also received considerable attention in the literature (Bird and Rowlands 2002). A key element of IMF mission is precisely to restore the investor's confidence. Still, the empirical results are mixed. For example, Edwards (2006) shows that IMF programs generate net outflows of portfolio while Jensen (2004) finds similar effects for foreign direct investments. Eichengreen and Mody (2000) provide evidence that IMF lending decreases bond spread while Cottarelli and Giannini (2002) claim that there is no such effect. Dreher and Walter (2010) find that the existence of an IMF-supported program in the previous five-year period reduces the probability of a future currency crisis. Regarding the banking sector, Papi et al. (2016) show that countries participating in IMF-supported arrangements are less likely to experience a banking crisis.

Our paper is also related to the research area concerned with the business cycle fluctuation and their sources. Scholars have tried to shed some light on the question of which source (external vs internal) contributes more to the cyclical fluctuations. For example, Ahmed and Park (1994) examine the impact of external and country-specific shocks on output, inflation and trade balance of each of the seven OECD countries. Using VAR models, Loayza and Raddatz (2007) examine how domestic characteristics influence the external vulnerability. Kim (2001) finds that US expansionary monetary policy shocks lead to booms in the non-U.S. G-6 countries. Canova (2005) analyzes whether and how US shocks are transmitted to eight Latin American countries and he finds that US disturbances explain a large share of the Latin America variability; he also claims that the monetary channel plays a more important role compared to the trade channel. Georgiadis (2015) assesses that global spillovers from identified US monetary policy shocks have relevant output effects to the rest of the world and the magnitude of these effects depends on country characteristics such as the trade integration, financial openness, exchange rate regime, labor market rigidities, etc.

In a globalized world where shocks and crises are frequent events, evaluating the performance of an important global actor (such as the IMF) in helping countries to protect themselves against adverse exogenous shocks is a subject of topical interest and relevance.

1.3 Methodology and model specification

In order to study the sensitivity to external shocks for a large number of countries, a multi-country model is preferred as the contemporaneous and lagged inter-dependencies among countries are accounted for. In the current analysis, this task is not possible for different reasons. First of all, the quality and availability of data among the 165 countries analyzed are highly heterogeneous. Second, many countries in our sample experienced episodes of hyperinflation, exchange and currency crises and modeling the corresponding domestic time series is hardly possible.

1.3.1 Empirical model

Following Canova (2005) we proceed on a bilateral basis, with the fixed (among countries) external block on one side and one domestic country at a time on the other. The external block includes 3 US variables (US GDP, US CPI inflation and Federal Reserve Interest rate) and the world oil price inflation; while the domestic block includes from 2 to 6 variables (GDP, CPI inflation, Trade, Interest rate, Reserve, Exchange rate) depending on the data availability. In this way, we simplify a lot the model; yet the correlation between the US and the domestic country is expected to be unidirectional and any sort of possible feedback within countries, others than US is excluded from the analysis.

In order to test our hypothesis that participation in IMF arrangements reduces the external vulnerability we set up a model for the domestic economies, taking as exogenous the external block shocks.

Therefore we consider a bivariate block VAR model:

$$\begin{bmatrix} y_t \\ w_{it} \end{bmatrix} = \begin{bmatrix} B(L)_{11} & 0 \\ B^i(L)_{21} & B^i(L)_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ w_{it-1} \end{bmatrix} + \begin{bmatrix} e_t \\ \epsilon_{it} \end{bmatrix} \tag{1.1}$$

where y_t represents the external block of variables and w_{it} represents the domestic variables of country i, and $(e_t\ \epsilon_t\ )\text{'}\sim(0, \varSigma_i)$, $\Sigma_i = \{\Sigma_e,\ \varSigma_\epsilon\}$.

Finally, let the model be described in a compact form by the underlying formula:

$$Y_i \quad = \quad B_i X_i + u_{it} \tag{1.2}$$

where $Y_i = \begin{bmatrix} y_t \\ w_{it} \end{bmatrix}$, $B_i = \begin{bmatrix} B(L)_{11} & 0 \\ B^i(L)_{21} & B^i(L)_{22} \end{bmatrix}$, $X_i = \begin{bmatrix} y_{t-1} \\ w_{it-1} \end{bmatrix}$ and the subscript i denotes the country specific variation of the domestic block.

1.3.2 Identification strategy

To identify the VAR model correctly and allow for meaningful interpretation of the variance decomposition we need to assign a number of restrictions on the coefficients. The strategy we adopt is to combine sign restrictions method (for the external block) with the

Table 1.1: Sign restriction summary. The 'x' indicates that there is no restriction on the response of a variable to a shock, while '+/-' indicates positive/negative response

	Y	π	R	oil	oil-π
Non-oil supply side	-	+	x	x	-
Real demand	+	+	+	x	x
Monetary policy	-	-	+	x	x
Oil	-	+	x	x	+

Cholesky decomposition (for the domestic block). Sign restrictions allows us to disentangle the 'supply', 'demand', 'monetary policy' and 'oil ' shocks and are imposed on the contemporaneous impact matrix.

Following Barnett et al. (2010) we assume that a real oil price shock decreases the US GDP, increases inflation and increases real oil price inflation while a negative supply shock generates an increase in US inflation, decreases US output and leads to a fall in real oil price inflation. This last effect is caused by the fact that this shock is assumed to push up the general price inflation more than the increase in the nominal oil price inflation because the negative supply shock implies a decrease in production capacity which in turn depresses the demand for energy. We also assume that a demand shock moves output, inflation and interest rate in the same direction while a restrictive monetary policy leads to a rise in the interest rate and a decrease in both output and inflation. The domestic block variables are identified through Cholesky decomposition. Causal ordering of the variables used in this work as in 1.3, stems from Canova (2005) and Eichenbaum and Evans (1995). [1]

$$\begin{bmatrix} GDP_{US}(log * 100) \\ CPI_{US}(\%) \\ R_{US} \\ Oil_{Inflation}(\%) \\ GDP_{domestic}(log * 100) \\ CPI_{domestic}(\%) \\ Trade_{domestic}(log(Exp/Imp) * 100) \\ R_{domestic} \\ Reserve_{domestic}(log) \\ Exchange_{domestic} \end{bmatrix} \tag{1.3}$$

To obtain the impact matrix we start by calculating the Cholesky decomposition of the (10x10) Σ matrix. We then take the QR decomposition of a 4x4 random matrix which we

[1] Although the domestic shocks are not of direct interest in our analysis, the identification of such shocks is necessary for a meaningful interpretation of the forecast error variance decomposition which is essential in our study.

append on Q, a 10x10 identity matrix. Finally, we multiply the modified Q matrix with the Cholesky decomposition of Σ and we check the sign compliance as in Table 1.1

1.3.3 Model estimation

We estimate the empirical model using Bayesian methods. In particular, we employ Gibbs sampling to simulate draws from the posterior distribution (Kim and Nelson 1999; Blake and Mumtaz 2012).

In Bayesian VAR analysis, the choice of the prior may be problematic. We impose small open economy restrictions which imply that shocks to the domestic economy do not affect the external variables. For this purpose, an appropriate prior is the Independent Normal Inverse Wishart prior. This prior involves setting the prior for the VAR coefficients and the error covariance independently. The independent Normal-Wishart prior allows us to incorporate these restrictions into the VAR model by imposing a prior mean for all coefficients equal to zero and the covariance of this prior as a diagonal matrix which takes value 1 for all elements except for the elements corresponding to $B_{12} = 0$ in 1.1. The elements corresponding to these coefficients are set to a very small number, therefore, the prior mean of zero is imposed tightly for them.

Following Banbura et al. (2010), for the remaining coefficients we impose a natural conjugate prior for the parameters via dummy observations:

$$Y_{D,1} = \begin{pmatrix} \frac{diag(\gamma_1\sigma_1...\gamma_N\sigma_N)}{\tau} \\ 0_{N\times(P-1)\times N} \\ .... \\ diag(\sigma_1....\sigma_N) \\ .... \\ 0_{1\times N} \end{pmatrix}; \; X_{D,1} = \begin{pmatrix} \frac{J_P\otimes diag(\sigma_1....\sigma_N)}{\tau} & 0_{NP\times 1} \\ 0_{N\times NP} & 0_{N\times 1} \\ .... & \\ 0_{1\times NP} & c \end{pmatrix} \tag{1.4}$$

where γ_1 to γ_N denotes the prior mean for the coefficients on the first lag, τ is the tightness of the prior on the VAR coefficients and c is the tightness of the prior on the constant terms. The prior means are determined as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable using a training sample. The σ_i scaling factors are chosen using the standard deviation of the error terms from the preliminary AR(1) regressions.

The posterior distributions for our VAR parameters as per 1.2 are:

$$p(B_i \mid \Sigma_i) \sim N(B_i^*, \Sigma_i \otimes (X_i^{*'} X_i^*)^{-1}) \tag{1.5}$$

$$p(\Sigma_i \mid B_i) \sim IW(S_i^*, T_i^*) \tag{1.6}$$

$$B_i^* = (X_i^{*\prime} X_i^*)^{-1}(X_i^{*\prime} Y_i^*) \tag{1.7}$$

$$S_i^* = (Y_i^* - X_i^* b_j)'(Y_i^* - X_i^* b_j) \tag{1.8}$$

with $Y_i^* = [Y_i; Y_{D,1}]$, $X_i^* = [X_i; X_{D,1}]$ and b_j is the draw of the VAR coefficients B reshaped to be conformable with $X_i{}^*$ while $T_i{}^*$ is the number of rows of $Y_i{}^*$.

Given the quarterly frequency of the data, in choosing the lag-length we test the system for a lag length up to four. The model selection procedure involves the estimation of models with L= 1,....4 and λ= 0.1,....0.5. We then select the VAR with the highest marginal likelihood, where L is the number of lags and λ is the parameter governing the overall prior tightness.

Several countries have more than one IMF arrangement over the course of time. This phenomena is known in the literature as "recidivism" and path dependency, meaning that countries with a longer history with the IMF are also more likely to receive programs in the present (Bird et al. 2004). In order to account for this effect we distinguish between two regimes, specifically under IMF program and not. We split the data accordingly and we estimate a model for each regime obtaining two indexes of external exposure. The difference in regimes is caused in a deterministic way by a known dummy variable equal to 1 if the country is under IMF program in a certain period and 0 otherwise. For countries that have only one regime the estimation is straightforward. Among the 165 analyzed countries, 77 have both regimes, 45 have only IMF regime and the remaining 43 have only the NO-IMF regime (see the appendix for a detailed list of the country-model structure).

The high heterogeneity in data availability and quality, required the adjustment of the model for each country. Therefore the range of time and the number of variables vary among countries. We aimed at preserving the baseline model as much as possible; however where data was poor the number of domestic variables was reduced and the oil shock was excluded from the external block. The choice of removing the oil variable is justified by our aim of maintaining the identification of the US supply, demand and monetary policy shock. Out of 165 countries, 70 countries have the complete model with 4 shocks and 6 domestic variables, while for the rest of countries we employed models with 3 shocks (US shocks) and 2 to 4 domestic variables, depending on the data quality and availability.

1.3.4 Index of external exposure

Given the heterogeneity in the model-structure, in order to obtain comparable results across countries we build the index of external exposure using pieces of variance decomposition as follows: (1) for each variable, we sum the share of forecast error variance explained by the external shocks; (2) we average this sum across domestic variables.

To control for the effects of the heterogeneity in the model specification, we conduct two additional sub-sample analyses. In the first one we restrict the regression exercise to countries with complete model while in the second one we consider the effect of external shocks on domestic GDP/IP.

1.3.5 Bilateral VAR vs alternative model specifications

In this section, we discuss two alternative approaches to our baseline model that are suitable for modeling data-sets with a large number of variables, namely the factor models and the global VAR (GVAR) model.

Factor models can be interpreted as shrinkage methods where a small number of estimated factors effectively summarize large amounts of information about the economy. The estimated factors can be used together with a standard structural VAR in a Factor Augmented VAR (FAVAR) model (Bernake et al., 2005; Stock and Watson, 2005;). The main advantage of using the FAVAR methodology in our application is that more plausible estimates for the external shocks could be obtained if they were extracted as factors of the entire data-set. However, we account for this effect in the sensitivity analysis when we replace the US variables with World variables in the external block.

On the other side, there is a quickly expanding literature on spillovers estimated by GVAR models. Briefly, GVAR models can be summarized as a two-step approach. In the first step, small scale country-specific models are estimated conditional on the rest of the world. In the second step, individual country models are stacked and solved simultaneously in a unique global VAR model (Chudik and Pesaran, 2014). Nevertheless, there are two reasons we consider the bilateral VAR a more appropriate choice for our empirical exercise. First, GVAR models are very useful for modeling the links between countries while taking into account how the rest of the world behaves but this goes beyond the purpose of our study. The second reason is that to the best of our knowledge there are no GVAR applications that accommodate unbalanced panels and trying to provide such an extension could be technically challenging. This represents an important restriction for our analysis since many of the countries that are highly indebted with the Fund have poor data availability. Focusing on limited, balanced data could lead to a loss in relevant information for the

Table 1.2: Summary of countries by income group

Income group	N.
High-income: non-OECD	20
High-income: OECD	32
Low-income	24
Lower middle-income	44
Upper middle-income	45

objective of our paper.

1.4 Data

For this empirical application, we construct an original time series database of quarterly observations for 165 countries from 1957 to 2014 employing three different sources. For the external block series, we used the Federal Reserve Economic data while for the domestic variables we combined Global Financial Data with International Financial Statistics. The sample period differs across countries depending on data availability and it typically covers the last 45 years for developed countries, the last 20 years for most of the developing countries and the last 10 years for few countries with poor data availability.

The observations are divided in two categories, the external block and the domestic block. The external data contains a measure of the real activity (log of US GDP), US CPI inflation (%), the Federal Fund Rates (%) and the oil price inflation (%). The domestic economy dynamics are captured by the log of real activity (GDP or Industrial production index), CPI inflation (%), a trade measure (log of the exports/imports ratio), interest rate (%), reserves (log) and exchange rates. Following Canova (2005), all the series are detrended and seasonally adjusted (except for the interest rates series). The income group classification of the countries in our sample is presented in Table 1.2.

1.5 Comparative analysis results

In order to conduct the empirical analysis, we estimate the model separately for each of the 165 countries in the sample. The model is estimated using Bayesian methods, thus the vulnerability index is constructed using the mean of the distribution of the variance decomposition.

In Table 1.3 we provide preliminary results for income-based groups. From the World Bank income classification we obtain 5 categories of countries: High-Income OECD, High income Non-OECD , Low-income, Lower-middle income and Upper-middle income. The

Table 1.3: External vulnerability index by country group

Q	Country group	NO IMF	IMF
1	High-Income:OECD	7.81269	11.76528
8	High-Income:OECD	12.66859	8.59872
40	High-Income:OECD	11.61318	8.54161
1	High-Income:non-OECD	8.6763	11.58385
8	High-Income:non-OECD	8.37996	9.68091
40	High-Income:non-OECD	8.20721	8.98475
1	Low -income	9.06413	3.64066
8	Low-income	4.72437	3.66155
40	Low-income	4.66688	3.47926
1	Lower middle-income	7.08792	5.3954
8	Lower middle-income	10.23458	6.12104
40	Lower middle-income	9.62306	5.62749
1	Upper middle-income	9.50927	7.35017
8	Upper middle-income	13.32759	9.95218
40	Upper middle-income	12.44774	9.64606

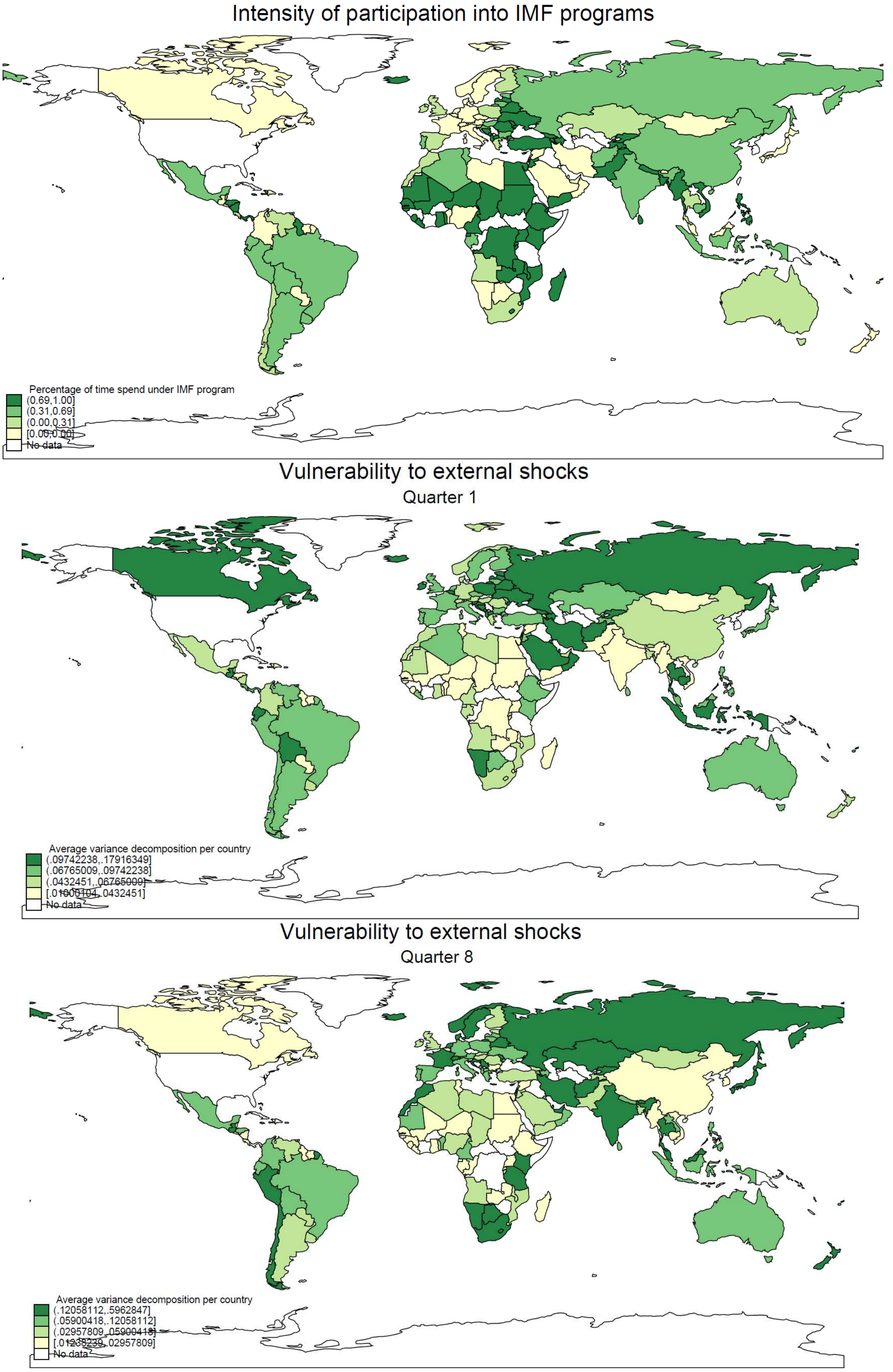
advanced OECD countries have a smaller mean for the IMF group, except for the first quarter while in the non-OECD group the opposite effect is observed. One possible explanation for this higher macroeconomic vulnerability for advanced Non-OECD countries while under IMF loan could be the self-selection issue as countries recur to IMF programs when they already face economic difficulties. This effect is enhanced in the case of advanced economies which are, in general, less likely to ask for IMF loans, except for situations of severe economic conditions. Focusing on the Low-income group, the IMF results are slightly smaller for all time-horizons, but the values in both groups are much below the average. One would expect low-income countries to display higher vulnerability. However, the exposure to external shocks depends, among other things, on the country‘s openness, trade intensity and financial development. Hence, a low-income country less integrated into the global financial markets will be less exposed to the external shocks (Georgiadis 2015). Regarding the middle-income countries (upper and lower), the sensitivity to external shocks is smaller for the group under IMF arrangement. The difference goes from 2% in the first quarter and stays around 3-4 % in the medium and long-run horizons. It is interesting to see that for the upper-middle income group the values are systematically greater than for the lower middle-income one. This effect may be explained by the higher financial integration (of the upper-income group) which is associated with stronger spillover effects (Edwards 2007a).

In Figure 1.1, we report the single country results. For countries that have both regimes, IMF and NO IMF the average of the two indexes of vulnerability is reported. The IMF intensity index accounts for the weight of each regime.. In order to keep track of the impact of IMF programs on the vulnerability to external shocks, in the first map, Figure 1.1 plots the intensity of participation in IMF's lending programs (average over time). Since the range of time differs across countries, hence this map should not be considered as a general distribution of the IMF loans over time, but related to this specific exercise. The second and the third map present the vulnerability to external shocks after 1 and 8 quarters. The results for 40 quarters ahead are not reported for ease of exposition; however similar to the findings related to Quarter 8. The magnitude of the results is indicated in the legend. From the first map, we learn that African countries, Turkey, Pakistan and some East European countries are the most indebted with the Fund, followed by Latin America, China, Russia, and India, while almost all the developed countries have small or null participation in the IMF arrangements.

It is easy to visualize the negative relation between the IMF intensity and the vulnerability to external shocks by noticing the inverse relation of the color intensity in the first two maps. Some of the most affected countries by shocks to US economy and crude oil price are Canada, Russia, the Baltic countries, Saudi Arabia, Iran, Afghanistan, and Oman. The results are in line with our expectations since these countries are the major oil exporters while the US is one of the most important oil importers. Therefore, shocks to US economy and to the oil price affect these countries through both the price and the level of the oil export. For Canada, the geographic proximity to the US also plays an important role. Additionally, Saudi Arabia, Iran, and Canada have null participation in IMF programs while Russia and Afghanistan present a large exposure but medium participation into the Fund's programs. The African countries have a high rate of IMF participation and a very small sensitivity to the external shocks. The low external sensitivity might be linked to the fact that low-income countries are less integrated into the global market thus less exposed to exogenous shocks. Regarding the Latin America countries, a medium-high participation in IMF programs corresponds to a medium-high exposure to shocks. Considering the geographical proximity and the tight links of these countries to the US, without IMF presence we might have observed a much higher external vulnerability.

From the second and the third map we can say something more about the contemporaneous and medium term impact of the external shocks. There is a consistent increase in the magnitude of the spillovers effects when we move from short to medium term as external shocks need time to propagate in the domestic countries. Apart for the value increment, there are small differences regarding the African and Latin America countries, while Canada and China have completely absorbed the shocks after 8 quarters. The opposite effect is observed for India and South Africa who experienced a small effect of the

Figure 1.1: Vulnerability to external shocks and participation into IMF programs



shocks on impact but they are much more affected in the medium term.

The results of the BVAR model estimation confirm our hypothesis that on average countries under IMF program show a smaller external vulnerability.

1.6 Correlation vs. causation in the IMF program participation

The analysis conducted in the previous section leads to the conclusion that a smaller sensitivity to external shocks is observed for countries under fund-supported programs. Not much can be said about the direction of causality of the previous results. In order to refine our conclusions and shed some light on the effects of the IMF programs on the external vulnerability, in this section, we consider a cross-sectional regression approach in the spirit of Loayza and Raddatz (2007), Bianchi and Civelli (2014) and Georgiadis (2015).

1.6.1 Empirical model

We estimate the following model:

$$v_i^h = \alpha + \beta_1 X_i + \beta_2 IMF_i + \varepsilon_i \tag{1.9}$$

where ${v^h}_i$ is the index of external exposure for country i, over the forecasting horizon h which can take the values of 1, 8 and 40. For countries that have both regimes, with and without the program, we use the average across regimes of the vulnerability indexes. The weight of each regime is captured by the intensity of IMF participation. The variables on the right hand side of 1.9 are averages over time for the sample for which data is available for each individual country. Specifically, X_i is a vector of control variables considered to be determinants of the external vulnerability (Loayza and Raddatz, 2007, Briguglio et al. 2009, Georgiadis 2015) and includes GDP per capita, FDI (% of GDP), trade (% of GDP) and Chinn-Ito index (KOPEN) of financial openness. Data on Chinn-Ito index comes from web.pdx.edu, while all the other variables are taken from World Bank official site. To capture the IMF participation we propose two different specifications. In the first one, IMF is a dummy variable which takes value 1 if the country i has ever been under IMF program and 0 otherwise. In the second specification, IMF is a measure of the intensity of participation in Fund‘s supported arrangements and is calculated as the percentage of time spent under IMF program in the sample available for each country; it can take values from 0 (no IMF program at all) to 1 (under IMF program for the entire time horizon considered). We are left with 161 observations for each of the 5 time horizons considered.

1.6.2 IV identification scheme

In order to assess whether participation in IMF loans decreases the vulnerability to external shocks of member countries, we have to sort out the direction of causality. The presence of the Fund in a country is more likely during periods of turmoil which can be associated with higher vulnerability to non-domestic developments; thus the OLS model can be biased due to potential endogeneity of IMF programs. Therefore in addition to the linear regression model we estimate also an IV model.

In the spirit of Barro and Lee (2005) we instrument IMF participation with the size of a country‘s quota at the IMF. The quota is the basis for determining voting power and also matters directly for the amount of lending available to a member. The quota is currently calculated as a weighted average of variables such as GDP, openness, international reserves and macroeconomic variability measured as volatility of current receipts and net capital flows to an economy. We argue that within the Fund, members are divided in two main categories, debtors and creditors. The advanced countries hold around 50% of the quotas and are the creditors, with almost no use of IMF‘s resources since 1978. Therefore, higher quota should imply a higher probability of being in the category of the creditors and consequently a smaller participation in IMF arrangements. Moreover, small (often underrepresented) countries are more likely to receive access to IMF resources because the amount of resources involved is less costly for the membership and less likely to lead to crowding out of access to funds. As such, we expect our instrument to be relevant with a negative sign in the first stage regression [2].

There could be a question on the exogeneity of the IMF quota instrument as it applies to external exposure instead of GDP growth rates. One could argue that advanced economies get higher quotas, are less likely to participate in IMF programs but they are also more interconnected and hence more sensitive to US shocks compared to the less developed countries. As mentioned in Georgiadis (2015) the impact of higher trade integration on spillover effects is ambiguous while financial integration can be associated with higher probability of contagion. However, developed countries have also stronger macroeconomic determinants therefore a higher ability to filter the external shocks; this later type of endogeneity would bias results against the negative impact of IMF interventions on external exposure. Moreover the preliminary results presented in section 5 show that

[2] Barro and Lee (2005) employ the size of the IMF quota as an instrument for IMF participation suggesting a positive impact of the IMF quota on the probability of receiving the loan but they present a completely different scenario. First of all, they use a panel data hence they account for the evolution over time of the participation into the Fund‘s programs. Second, they model the participation in an IMF program as a joint decision between a member country and the IMF, hence, they control for the economic difficulties experienced by countries that determine the need of the loan, such as banking crises, currency crises, etc. They finally claim that if a loan is needed, a higher IMF quota implies a higher bargaining power , hence a greater probability of receiving the loan.

both developed and developing countries are exposed to external shocks, therefore there is no clear relation between the level of development of a country and its vulnerability to shocks captured by our index. Additionally the quotas do not necessarily capture the economic relevance of members in a clear and objective way. The initial quotas of the original members were determined at the Bretton Woods Conference in 1944 and they are quite persistent over time; although quotas are revised in general terms every 5 years, there are still IMF members with unusually high or low current quotas relative to their economic size. For example, Barro and Lee (2005) find that the most over-weighted quotas are United Kingdom, France, Russia, Venezuela while the most under-weighted ones are China and South Korea. Finally, we are not aware of any evidence supporting a direct linkage between IMF quota and the external exposure of a country.

1.6.3 Results

Table 1.4 presents the results of the linear regression model for the two different measures of the participation into IMF programs, namely IMF and IMFintensity. The dependent variable is the log of the external vulnerability index, for each of the three forecast horizons. We recall that IMF is a dummy taking value 1 if the country has ever had an IMF loan and 0 otherwise while IMFintensity captures the amount of time spent under an IMF program in the range of time considered for each member. Except for the first quarter, the IMF dummy variable is always negative and significant at 95% level suggesting that countries that had at least 1 IMF loan are less sensitive to external shocks. In the second specification, the IMFintensity coefficient is negative and significant all the time at 99% level for all horizons. Hence, a longer period under IMF programs corresponds to a smaller sensitivity to non-domestic shocks.

These results support the idea that the IMF arrangements act as a shield against non-domestic shocks. In line with the previous literature, in the control group, the most important variables are the index of financial integration (KOPEN), positive and significant and the trade intensity (Trade) which is negative and significant. Giorgiadis (2015) points out that trade integration is a crucial determinant of the business cycle synchronization and spillovers, but it could also dampen the effects of exogenous shocks by rendering current account reversals in response to adverse US monetary policy shocks less probable, or it could mitigate the effects on growth once the current account reversal took place. Moreover, if the expenditure effect associated with a rise in exports to the US in response to the appreciation of the US currency, prevails on the expenditure-reducing effect caused by an increase in the global interest rate, more integrated economies in global trade should be less sensitive to spillover effects. Financial integration (here captured by the financial openness) is associated in the literature with more sudden stops and current account re-

Table 1.4: OLS regression results

VARIABLES	(Q1) Vulnerability	(Q8) Vulnerability	(Q40) Vulnerability
IMF	0.0829	-0.337**	-0.323**
	(0.106)	(0.165)	(0.161)
KOpen	0.00453***	0.00223	0.00230
	(0.00105)	(0.00171)	(0.00167)
logGDP	0.0424	-0.0213	-0.0279
	(0.0458)	(0.0652)	(0.0621)
logTrade	-0.184***	-0.0834	-0.0812
	(0.0426)	(0.0622)	(0.0601)
logFDI	0.0507	0.0140	0.0340
	(0.0441)	(0.0734)	(0.0695)
Constant	-2.774***	-2.279***	-2.405***
	(0.344)	(0.508)	(0.489)
Observations	161	161	161
R-squared	0.179	0.061	0.064

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(Q1) Vulnerability	(Q8) Vulnerability	(Q40) Vulnerability
IMFintensity	-0.258**	-0.551***	-0.558***
	(0.123)	(0.186)	(0.180)
KOpen	0.00316***	0.00165	0.00164
	(0.000960)	(0.00172)	(0.00169)
logGDP	0.0436	-0.00545	-0.0123
	(0.0428)	(0.0644)	(0.0607)
logTrade	-0.168***	-0.0604	-0.0576
	(0.0428)	(0.0643)	(0.0619)
logFDI	0.0783*	0.0290	0.0507
	(0.0422)	(0.0747)	(0.0702)
Constant	-2.668***	-2.424***	-2.539***
	(0.339)	(0.502)	(0.481)
Observations	161	161	161
R-squared	0.199	0.089	0.096

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

versals (Edwards 2007a; Calvo et al. 2008). The negative consequences are more severe in financially integrated and open economies, hence financial integration may be associated with greater contagion effects as reflected in our results (Edwards 2004, 2007a). Regarding the control variables, only two of them are significant and just for the first quarter, showing that these variables affect the ability of a country to avoid and filter the exogenous shocks, but not the capacity to recover once the adverse effects occurred, while the IMF intensity has a negative and significant impact in all horizons.

Nevertheless, the previous results do not account for the bias due to potential endogeneity of the IMF programs. In Table 1.5 we present the results of the IV regression where IMF participation variable is instrumented by the size of the IMF quota. In the first stage regression the IMF quota is always significant at 95% for the IMF dummy specification and at 99% for the IMF intensity specification; hence the relevance of the instrument is verified. Following, the IV regression results reinforce our hypothesis that IMF arrangements enhance the capacity of members to protect themselves against external shocks. The sign of the coefficients is mainly unchanged. IMF and IMFintensity are significant at 95% and respectively 99% level and as expected, we gain a lot in the magnitude of the point estimates. If in the linear regression model, a 1% increase in the IMF participation decreases the sensitivity to external shocks by approx. 0.3% for the first specification of the IMF participation variable and respectively 0.5% for the second one, in the IV regression, a 1% increase in the IMF participation intensity reduces the external exposure by 3% and respectively 2.5%.

1.6.4 Robustness to the model heterogeneity

Due to the heterogeneity in data availability and quality, we estimated different country-specific VAR models and this approach might raise the question whether the external exposure indexes are comparable across countries. In order to address this issue we conduct two different checks reported in Table 1.6.

Table 1.5: IV regression results

VARIABLES	(First stage) IMF	(Q1) Vulnerability	(Q8) Vulnerability	(Q40) Vulnerability
IMF		-1.279*	-3.361**	-3.321**
		(0.716)	(1.692)	(1.688)
KOpen	-0.00420***	-0.00166	-0.0115	-0.0113
	(0.000779)	(0.00380)	(0.00872)	(0.00871)
logFDI	0.0617	0.167*	0.272	0.290
	(0.0442)	(0.0988)	(0.242)	(0.237)
logTrade	0.0163	-0.155**	-0.0197	-0.0179
	(0.0373)	(0.0636)	(0.123)	(0.120)
logGDP	-0.0325	0.00756	-0.0986	-0.105
	(0.0300)	(0.0608)	(0.125)	(0.124)
IMFquota	-0.0678**			
	(0.0299)			
Constant	0.876***	-1.792***	-0.0981	-0.243
	(0.280)	(0.653)	(1.436)	(1.438)
Observations	161	161	161	161
R-squared	0.215			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(First stage) IMFintensity	(Q1) Vulnerability	(Q8) Vulnerability	(Q40) Vulnerability
IMFintensity		-0.968***	-2.542***	-2.512***
		(0.373)	(0.878)	(0.875)
KOpen	-0.00338***	0.000445	-0.00598	-0.00585
	(0.000712)	(0.00199)	(0.00433)	(0.00432)
logFDI	0.0481	0.135**	0.187	0.206
	(0.0411)	(0.0643)	(0.155)	(0.148)
logTrade	0.0481	-0.130**	0.0480	0.0489
	(0.0314)	(0.0521)	(0.0996)	(0.0965)
logGDP	0.00390	0.0529	0.0206	0.0132
	(0.0327)	(0.0458)	(0.0971)	(0.0931)
IMFquota	-0.0897***			
	(0.0246)			
Constant	0.382	-2.542***	-2.070***	-2.191***
	(0.241)	(0.383)	(0.705)	(0.684)
Observations	161	161	161	161
R-squared	0.224	0.021		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.6: IV results. Model heterogeneity

Real activity vulnerability

VARIABLES	(First stage) IMFintensity	(Q1) Real activity (log)	(Q8) Real activity (log)	(Q40) Real activity (log)
IMFintensity		-0.676	-1.224*	-1.217*
		(0.558)	(0.740)	(0.698)
KOpen	-0.0045***	0.00141	-0.00237	-0.00239
	(0.00126)	(0.00415)	(0.00558)	(0.00536)
logFDI	-0.0042	0.0701	0.0185	0.0803
	(0.04009)	(0.0692)	(0.127)	(0.107)
logTrade	0.0609	0.0158	0.0462	0.0493
	(0.0406)	(0.0824)	(0.101)	(0.0897)
logGDP	0.03111	0.169*	0.149	0.110
	(0.0245)	(0.0875)	(0.109)	(0.0984)
IMFquota (log)	-0.1044***			
	(0.0245)			
Constant	0.1542	-3.331***	-2.527***	-2.732***
	(0.2285)	(0.450)	(0.610)	(0.548)
Observations	101	101	101	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Complete model

VARIABLES	(First stage) IMFIntensity	(Q1) Vulnerability	(Q8) Vulnerability	(Q40) Vulnerability
IMFIntensity		-0.0932	-1.213*	-1.237*
		(0.327)	(0.700)	(0.690)
KOpen	-0.00446***	0.00315	-0.00235	-0.00235
	(0.000551)	(0.00236)	(0.00531)	(0.00526)
logFDI	-0.00418	0.0856*	0.0492	0.0895
	(0.0175)	(0.0438)	(0.108)	(0.104)
logTrade	0.0609***	-0.0666	0.0458	0.0505
	(0.0177)	(0.0447)	(0.0913)	(0.0869)
logGDP	0.0311**	0.0220	0.124	0.107
	(0.0147)	(0.0505)	(0.102)	(0.0965)
IMFquota (log)	-0.104***			
	(0.0107)			
Constant	0.154	-2.793***	-2.622***	-2.773***
	(0.0997)	(0.238)	(0.545)	(0.525)
Observations	101	101	101	101
R-squared	0.278	0.120		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the first exercise we restrict the cross section regression to a sub-sample of countries that contain GDP/IP in their model and we calculate the index of external exposure as the share of the variance decomposition of domestic GDP/IP explained by non-domestic shocks. The sample includes 101 observations out of which 70 have the complete 4x6 model (4 external shocks and 6 domestic variables), 19 have 3x4 models and the rest have 3x3 or

3x2 models. Mainly, IMFintensity is still negative and significant at 90% level[3].

In the second check we reduce the sample to a set of economies for which the model specification is sufficiently homogeneous, i.e. we consider only the individuals with 4x6 and 3x4 models. The sub-sample contains 101 observations with 70 complete models and 31 with 3x4 models. IMF intensity is always negative and significant in the medium and long run horizon.

To sum up, the main conclusion of this analysis is that a higher participation rate in IMF programs significantly decreases the sensitivity to external shocks. The magnitude of the estimates increases when the endogeneity of IMF intervention is addressed. Finally, the results are robust to the heterogeneity in model specification.

1.7 Summary

IMF has been a relevant actor in shaping the global economy since the end of the World War II and its role and objectives evolved together with the global system. Nowadays, one of the Fund‘s primary purposes consists in "advising member countries on economic and financial policies that promote stability, reduce vulnerability to crises, and encourage sustained growth and high living standards"[4]. However, very little empirical literature analyzed the efficiency of the Fund in helping countries to reduce their vulnerability to external shocks. Trying to fill part of this gap, we address this explicit, although less often studied goal of the IMF programs.

We proposed a bilateral BVAR model considering a sample of 165 countries with a varying range of time among countries due to the data availability and quality. We built a measure of external exposure with pieces of variance decomposition, focusing on the average effect of external shocks on domestic variables.

The BVAR results showed that countries under Fund-supported loans have a smaller sensitivity to external shocks compared to countries without IMF program.

We then ran a cross section analysis to test the effect of participation in IMF programs on the external exposure. We controlled for the potential endogeneity instrumenting the IMF participation with the size of IMF quota. We found that IMF participation significantly decreases the external vulnerability of member countries. A number of robustness checks reinforced our results.

Although several studies claim that IMF interventions tend to have adverse economic consequences, this analysis showed that the Fund is efficient in helping member countries to smooth the adjustment to non-domestic shocks.

[3] See the appendix for OLS results of this exercise
[4] www.imf.org

Chapter 2

Connectedness and spillovers in recession and boom.

2.1 Introduction [1]

Enhanced correlation of GDP growth rates across countries during the global financial crisis has spurred renewed interest of policymakers and academics in the international business cycle and cross-country co-movements in economic activity. The literature supports the evidence of commonality in macroeconomic fluctuations across countries, particularly for advanced economies (Kose et al., 2003; Canova et al., 2007; Diebold and Yilmaz, 2013; Antonakakis et al., 2016), with two main explanations put forward. The first one focuses on the role of global common shocks that hit different countries simultaneously while the second is based on the observation that specific shocks that originate in one country spill over to foreign economies via trade and financial linkages.

The changing behaviour of macroeconomic aggregates in good and bad times is a further issue that has attracted the attention of scholars. In particular, the theoretical literature supports the idea that the business cycle is asymmetric, with recessions and expansions characterized by swings of different magnitude (see Neftci, 1984; Morley and Piger, 2012;Vavra 2013; Bloom, 2014). Other studies instead focused on analyzing the changes in the effects of monetary and fiscal policy during recessions and booms (Auerbach and Gorodnichenko, 2011; Mumtaz and Surico, 2015; Tenreyro and Thwaites, 2016). Within this, an emerging strand provides theoretical background to the increased cross-country co-movement in recessions (see Perri and Quadrini, 2017; Dedola and Lombardo, 2012).

Despite these findings, there is little empirical evidence on why and the extent to which state dependency of international synchronisation manifest itself in practice. This is

[1] This chapter has been published as Miescu, M.S., 2018. Together in bad times? Connectedness and spillovers in recession and boom. The Manchester School.

in part due to the fact that most of the existing empirical research is based on linear models which, by construction, do not account for state dependency of the parameters. As such, the main objective of this study is to provide evidence on the asymmetry of synchronization in economic activity in developed countries across different phases of the business cycle. To this end, we calculate an index of global economic connectedness for seven advanced economies, in line with what proposed by Diebold and Yilmaz (2014) (hereafter DY index) and gauge its behaviour in a regime switching framework.

In addition to this, recent studies have also heightened the importance of financial shocks and their impact on real activity (see Kiyotaki and Moore, 2012; Jermann and Quadrini, 2012; Gertler and Karadi, 2011) while other researchers investigated the reasons behind international co-movements in inflation (see Ciccarelli and Mojon, 2010; Mumtaz et al., 2011; Mumtaz and Surico, 2012). As emphasized in Cotter et al. (2017) disregarding the linkages between the real, financial and nominal sides of the economy would provide an incomplete picture of the structure of spillovers and consequently of the co-movement in economic activity. In particular, negative conditions in financial markets can have clear adverse effects on the real side of the economy through a reduction in the willingness of financial firms to provide credit causing a tightening in the financial conditions which in turn reduces corporate investment (Ivashina and Scharfstein 2010). Similarly, macroeconomic adverse conditions can affect financial markets by increasing corporate defaults or suppressing firms' equity values. Regarding the interdependence in nominal and real variables, Mumtaz et al. (2011) jointly identify global factors in inflation and output and find that the world factor is more important in explaining the nominal dynamics than the real ones while Wang and Wen (2007) suggest that cross-country correlations in inflation are higher than cross-country correlations in output. On the theoretical side, Henriksen et al. (2009) have proposed a theory of international comovement in nominal variables based on technology spillovers. However, up to now the literature has not examined the asymmetry of the connectedness in financial and nominal variables across business cycle phases neither their interactions with the real side of the economy. Trying to fill this gap, in an extension of the baseline model, we adopt a mixed-variables approach in the spirit of Greenwood et al., 2015. Therefore, we draw further conclusions on the connectedness in financial and inflation variables and their interactions with the real side of the economy.

Our regime-switching model suggests that global connectedness is substantial and state-dependent, displaying significantly higher values in times of economic depression relative to upturns. This holds true particularly in the case of real variables such as industrial production. In contrast, while financial and inflation swings also tend to be highly synchronised across countries, they exhibit little variation with the business cycle. Instead, connectedness of inflation fluctuates over the forecasting horizon, displaying higher values in the long run and in boom periods; this finding is in line with the long-run objectives of the monetary policy which are better achieved in normal times when the central bankers do not have to undertake policies aimed at counteracting recessionary gaps. From a theoretical view, one potential explanation for our results comes from Perri and Quadrini (2017) who show that a global liquidity shortage caused by credit shocks can generate co-movement in real and financial variables across countries.

Our setting also allows us to (partly) analyse the drivers of cross-country co-movements in macroeconomic indicators. We find that shocks to financial variables tend to explain a large fraction of the connectedness observed in IP across advanced economies especially in times of recession. Finally, we obtain insightful country results. For example, we find that while Europe is more sensitive to spillovers from US and Japan, the opposite does not seem to hold true. In addition, a counterfactual simulation performed against real economic data shows that connectedness might have had a very important role in driving country specific economic fluctuations over the past. In a counterfactual world where shocks to US are switched off, IP growth of the remaining countries is more than 4% higher in recessions and 2-3% smaller in booms. Another message delivered by the counterfactual exercise is that accounting for the asymmetry across business cycle phases provides more accurate estimates of the impact of increased connectedness on IP variables.

There are several advantages of using a regime switching model relative to the rolling window approach often encountered in the DY connectedness literature. First of all, the regime switching setting explicitly models the state-dependency of the parameters while the rolling window technique captures the time variation in the parameters; as such the two methodologies provide different perspectives of the same phenomena. Second, the non-linear model allows for the endogenous switch in regimes, making it suitable for the analysis of the sign asymmetry of shocks while the linear framework implies symmetric effects of positive and negative shocks. Third, in the regime switching framework the periods of booms and busts are estimated within the model instead of being exogenously determined as it is the case in the rolling window scenario. Finally, although the rolling window approach has the advantage of being simple, it requires the choice of the window length which can affect the accuracy of the results if parameters are sensitive to the window‘s width; in change this choice is not required in the regime switching model. Nevertheless the non-linear framework comes at the cost of capturing only static state-dependent connectedness.

The contribution of our paper to the literature is threefold. First, by using a Threshold VAR model (hereafter TVAR) we account for the regime-dependency of macroeconomic connectedness of seven industrialized countries. Second, allowing for an endogenous switch in regimes, we capture the sign asymmetry of shocks and we show that negative innovations increase connectedness more than the positive ones. Finally, the Bayesian methodology employed in our empirical exercise is particularly attractive for estimating high-dimensional models. As such, we extend the benchmark model featuring IP as real activity variable to also include financial and nominal ones. With this extension we go beyond previous findings in the literature as we investigate the composition of the global connectedness index and its variation over the business cycle.

Given the large cross-country macroeconomic and financial linkages, knowing the extent to which cross-country connectedness is state-dependent and understanding better its sources and composition is not only relevant from an academic perspective but it also has important policy implications. Our results indicate that at times of economic downturn synchronization across countries increases significantly; thus more policy coordination might be necessary to better deal with such events. Additionally, our findings suggest that the nature of shocks (real or financial) matters to a large degree, and a better understanding of its relative implications could help policymakers to tailor their measures to account for the size, composition and behaviour of co-movement in economic activity. This would represent an important input for these policy instruments aimed at offsetting the impact of foreign shocks.

The remainder of the paper is structured as follows. In section 2 we discuss in depth the DY connectedness index. In sections 3 and 4 we present the methodology and the data used in the empirical exercise. In section 5 we illustrate our results and in section 6 we examine additional robustness checks. Section 7 concludes. We relegate to the appendix further details of the TVAR and Smooth Transition VAR models estimation and various directional and sensitivity analysis results.

2.2 DY connectedness index

Although connectedness represents a key concept in the understanding and measuring of risk, it is rather poorly measured (mainly through correlation-based measures) and incompletely defined. Building on Diebold and Yilmaz (2014), in this paragraph we introduce the DY index, a measure of connectedness grounded in modern network theory, linked also to the systemic risk literature.

DY approach consists in measuring the connectedness across different units using shares of forecast error variation due to shocks arising elsewhere. This definition is closely related to the econometric notion of variance decomposition which is a prominent tool in interpret-

Table 2.1: Connectedness table

	x_1	x_2	$\cdots$	x_N	**From Others**
x_1	d_{11}	d_{12}		d_{1N}	$\sum d_{1j}$, $j \neq 1$
x_2	d_{21}	d_{22}		d_{2N}	$\sum d_{2j}$, $j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d_{N1}	d_{N2}	$\cdots$	d_{NN}	$\sum d_{Nj}$, $j \neq N$
To Others	$\sum d_{i1}, i \neq 1$	$\sum d_{i2}, i \neq 2$	$\cdots$	$\sum d_{iN}, i \neq N$	$1/N \sum_{i,j=1}^{N} d_{ij}, i \neq j$

ing estimated linear or non-linear VAR models and it indicates how much of the forecast error variance of each variables in the model can be explained by shocks to other variables. Specifically, the H-step forecast error variance $d^{H}{}_{i,j}$ is the fraction of the i's H-step ahead forecast variance due to shocks in variable j. The full set of variance decompositions produces the connectedness table.

In Table 2.1, the N x N upper-left block contains a full variance decomposition matrix. In addition, the rightmost column contains row sums, the bottom row contains the column sums while the bottom-right element contains the grand average, in all cases for $i \neq j$.

For example, d_{21} indicates how much of the forecast error variance of variable x_2 is explained by shocks in variable x_1. In the "To Others" row, $\sum d_{i1}, i \neq 1$ shows how much of the variation in variables other than x_1 is explained by shocks in x_1, while in the "From Others" column, $\sum d_{1j}$, $j \neq 1$ shows how much of the variation in x_1 is explained by shocks occurring elsewhere. These values are defined as total directional connectedness from and to others. If we consider the difference between To and From others for a certain variable x_i, we get the Net directional connectedness which identifies whether the variable x_i is a shock "transmitter" or a shock "recipient". Finally, the global connectedness is given by the grand total of the off-diagonal entries in the variance decomposition matrix and gives a measure for the system-wide connectedness.

The methodology developed by DY is particularly appealing in the context of our analysis as it allows us to analyse how shocks in one country impact on other countries, both at pairwise and aggregate level. In the case of a standard linear VAR, the model estimation produces one connectedness table in the static analysis, or a time varying connectedness index if a rolling window approach is used. Alternatively, with the threshold model we obtain a variance decomposition matrix for each regime. As such, the main novelty introduced by our approach consists in estimating a state-dependent connectedness index.

2.3 Non-linear VAR models

Here we describe the econometric models used in the empirical exercise and the identification strategy.

2.3.1 Empirical models

Our analysis tests the hypothesis that there is a shift in the behaviour of macroeconomic variables across different phases of the business cycle. This makes using a constant parameter model an unsuitable option. One way to deal with the variation of parameters across expansions and recessions is by the mean of a "regime-switching" model, such as the TVAR or Smooth Transition VAR (hereafter STVAR). These models allow for different values of the parameters in each of a fixed number of regimes which is usually not observed by the econometrician.

TVAR model

Following Alessandri and Mumtaz (2017) in this section we introduce the TVAR model defined as:

$$Y_t = \left[c_1 + \sum_{j=1}^{P} B_{1,j} Y_{t-j} + \Omega_1^{1/2} e_t \right] \mathit{1}_{E(S)_t} + \left[c_2 + \sum_{j=1}^{P} B_{2,j} Y_{t-j} + \Omega_2^{1/2} e_t \right] (1 - \mathit{1}_{E(S)}) \quad (2.1)$$

for j=1..N and the change in regime is described through the indicator function $1_{E(S)}$ of the event S as follows:

$$\mathit{1}_{E(S)} = \begin{cases} 0 \iff Z_{t-d} \leq Z^* \\ 1 \iff Z_{t-d} > Z^* \end{cases} \quad (2.2)$$

Y_t={IP(US), IP(Japan), IP(UK), IP(Germany), IP(France), IP(Italy), IP(Spain)} is the $T \times N$ matrix of endogenous variables. We allow for regime-dependent heteroschedasticity captured by $\mathit{\Omega}_1$ and $\mathit{\Omega}_2$. Given the monthly frequency of data we choose a lag length p of 13. We have two additional specifications in which we combine IP with Stock Price Index (hereafter SPI) and IP with PPI. The model accommodates for two regimes determined by the level of the threshold variable Z_{t-d} relative to an unobserved threshold level Z^*. In our analysis the threshold variable is assumed to be the dth lag of the weighted average of IP growth while the delay d is unknown. Since the IP weights as a share of global IP are available from 1991 only while our sample starts in 1962, in constructing the threshold variable we propose two specifications (see Table 2.2). In the first one the weights reflect the relative GDP share in the world GDP which are available for the time period under analysis; in the second specification we use the country IP weights since 1991. The weights are normalized to sum to 1 in both specifications.

The threshold variable is assumed to cause the switch across regimes in an abrupt way and this might be considered a tight restriction. As an alternative we also examine a Smooth Transition VAR which allows for a gradual transition between the high and low IP growth regimes. The regimes identified by this specification are recessions and expansions.

The high number of the parameters to be estimated favors the choice of Bayesian methods for the estimation strategy. In the spirit of Banbura et al. (2010) and Sims and Zha (1998), we impose a natural conjugate prior for the parameters via dummy observations:

$$Y_{D,1} = \begin{pmatrix} \frac{diag(\gamma_1\sigma_1...\gamma_N\sigma_N)}{\tau} \\ 0_{N\times(P-1)\times N} \\ .... \\ diag(\sigma_1....\sigma_N) \\ .... \\ 0_{1\times N} \end{pmatrix};\ X_{D,1} = \begin{pmatrix} \frac{J_P \otimes diag(\sigma_1....\sigma_N)}{\tau} & 0_{NP\times 1} \\ 0_{N\times NP} & 0_{N\times 1} \\ .... & \\ 0_{1\times NP} & c \end{pmatrix} \tag{2.3}$$

where γ_1 to γ_N denotes the prior mean for the coefficients on the first lag, τ is the tightness of the prior on the VAR coefficients and c is the tightness of the prior on the constant terms. The prior means are determined as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable using a training sample. The σ_i scaling factors are chosen using the standard deviation of the error terms from the preliminary AR(1) regressions. As is standard in the literature, we set the overall tightness parameter τ to 0.1 (see Alessandri and Mumtaz, 2017; Robertson and Tallman, 1999). Finally the prior on the constant is imposed to 1. Additionally we introduce a prior on the sum of the lagged dependent variables by adding the following dummy observations:

$$Y_{D,2} = \frac{diag(\gamma_1\mu_1....\gamma_N\mu_N)}{\lambda};\ X_{D,2} = \begin{pmatrix} \frac{(1_{1\times P})\otimes diag(\gamma_1\mu_1....\gamma_N\mu_N)}{\lambda} & 0_{N\times 1} \end{pmatrix} \tag{2.4}$$

where μ_i denotes the sample means of the endogenous variables calculated using the training sample. As in Banbura et al. (2010) the tightness on the sum of coefficients is set to $\lambda = 10\tau$. Given the natural conjugate prior the posterior distribution takes the form:

$$p(B_i \mid \Sigma_i, Y_t, Z^*) \sim N(vec(B_i^*), \Sigma_i \otimes (X_i^{*'} X_i^*)^{-1}) \tag{2.5}$$

$$p(\Sigma_i \mid B_i, Y_t, Z^*) \sim IW(S_i^*, T_i^*) \tag{2.6}$$

where

Table 2.2: Threshold variable weights

Country\Variable	GDP weights	IP weights
US	0.51	0.41
Japan	0.15	0.22
Germany	0.10	0.13
UK	0.07	0.07
France	0.07	0.05
Italy	0.06	0.07
Spain	0.04	0.05

$$B_i^* = (X_i^{*'} X_i^*)^{-1} (X_i^{*'} Y_i^*) \tag{2.7}$$

$$S_i^* = (Y_i^* - X_i^* b_j)'(Y_i^* - X_i^* b_j)$$

for i=1,2 denoting the two regimes ; Y*=[Y_t; $Y_{D,1}$;$Y_{D,2}$], X* =[X_t; $X_{D,1}$; $X_{D,2}$] where $X_t = (1, Y'_{t-1}, ..., Y'_{t-j})$' is the K×1 vector of regressors, with $K = (N \times j + 1)$, , $B_i = vec\left([c; B_1; B_2; ..B_j]\right)$, b_j is the draw of the VAR coefficients B_i reshaped to be conformable with X_i^* while T_i^* is the number of rows of Y_i^*. We impose a normal prior for $Z^* \sim N(0, 10)$. Considering the scale of the threshold variable used in our paper, this represents a quite loose prior. We assume a flat prior for the delay parameter d but we limit its values between 1 and 12.

To simulate the posterior distribution of the unknown parameters we employ Chen and Lee (1995) Gibbs sampler with a Metropolis - Hastings step (see Algorithm 1 in the Appendix for details). Finally, we validate the choice of the empirical model in a model comparison analysis and a convergence diagnostic test. Results are reported in Table S3 and respectively Figure S17.

STVAR

The advantage of the TVAR models consist in their ability to capture changes in both volatility of the parameters and the strength of the shock propagation mechanism across different states of the economy. However, the TVAR imposes quite tight restrictions on the relation between the threshold variable and transition across regimes. Specifically, the threshold variable is assumed to cause the switch across regimes in a deterministic way. Therefore, an alternative to the TVAR model is represented by the STVAR as follows:

$$Y_t = \left[c_1 + \sum_{j=1}^{P} B_{1,j} Y_{t-j} \right] + \left[c_2 + \sum_{j=1}^{P} B_{2,j} Y_{t-j} \right] \pi_t + \varepsilon_t \tag{2.8}$$

$$\varepsilon_t \sim \mathrm{N}(0,\Omega)$$

The Transition function Π is defined as

$$\pi_t = [1 + exp(-\lambda \times (Z_{t-d} - Z^*)]^{-1} \tag{2.9}$$

where $\lambda > 0$ is the smoothness parameter, Z is the threshold variable defined as in 2.2 and Z^* is the unobserved threshold level.

The STVAR is very similar to the TVAR model but it allows for gradual transition between the two different regimes as determined by the transition function $\pi(\lambda, Z_{t-d}, Z^*)$. The regime is determined by the level of the threshold variable Z_{t-d} in the transition function π with the delay d, relative to the unknown threshold level Z^*.

For estimation aims, the STVAR model can be rewritten as:

$$Y_t = B_1 X_t + [B_2 X_t]\, \pi_t + \varepsilon_t \tag{2.10}$$

where $X_t = (1, Y'_{t-1}, ..., Y'_{t-j})$' is the K×1 vector of regressors, with K=$(Nj + 1)$; B_i =$[c_i, A_{i,1}, ..., A_{i,j}]$ is the N×K matrix of coefficients and i=1,2 are the regimes.

In order to draw the state-dependent parameters we use the following formulas:

$$Y_{1t} = B_1 X_t + \varepsilon_t \tag{2.11}$$

$$Y_{2t} = B_2 X_t \pi + \varepsilon_t \tag{2.12}$$

where Y_{1t}= Y_t-$[B_2 X_t]\pi$ and Y_{2t}= Y_t-$[B_1 X_t]$;

The algorithm used to estimate the STVAR model, the priors and initial values are similar to the TVAR model. We have the additional prior for the smoothness parameter $\lambda \sim$gamma (25,0.2) and the MH step now consists in drawing two parameters, respectively the threshold level Z^* and the smoothness parameter λ (see Algorithm 2 for details)[2] . Results of the STVAR model are discussed in the sensitivity analysis section. Specifically, Figure S4 reports the difference in the global connectedness across regimes, while FigureS5 , Figure S6 and Figure S7 describe the results for each of the three model specifications.

[2]This prior for λ insures that the regimes identified by the STVAR are consistent with the TVAR model. The Gamma distribution is consistent with the requirement of λ being positive.

2.3.2 Generalized identification

Koop, Pesaran and Potter (1996) show how the introduction of non-linearity in the model can cause the intrinsic linear properties of shocks and history dependence to be lost. Hence, traditional impulse response functions, which are neither shock (when suitably scaled) nor history-dependent are inappropriate in a non-linear framework such as ours; the Generalized Impulse Response Functions (hereafter GIRF) should be used instead. Specifically, these responses are defined as follows:

$$GIRF_t^S = E(Y_{t+k} \mid \Psi_t, Y_{t-1}^S, \mu) - E(Y_{t+k} \mid \Psi_t, Y_{t-1}^S) \tag{2.13}$$

where Ψ_t denotes all the parameters and hyper-parameters of the model, k is the forecasting horizon under consideration, S= 0,1 denotes the regime and μ is the shock. Equation 2.13 characterizes the GIRF as the difference between two conditional expectations, one in which we condition on the shock μ (the first term of 2.13), and the other term in which we assume the shock to be equal to zero. The estimation of the conditional expectations in 2.13 requires Monte Carlo simulations across a number of replications which in the current analysis is set to 35. Therefore, for each draw the impulse responses for each regime are calculated as the difference between the average across replications of the two conditional expectations. We define the shock as:

$$\mu_j^s = \Sigma_s v_j / \sqrt{\Sigma_{s,jj}} \tag{2.14}$$

where s identifies the regime (low or high output growth), j is the endogenous variable on which we apply the shock while v$_j$ is a $1 \times N$ selection vector with its jth element equal to unity and zeros elsewhere. Unlike the orthogonalized impulse response functions obtained with Cholesky decomposition, the GIRF are unique and are not affected by the reordering of the variables which is an appealing characteristic for our application.[3]

Another advantage of the GIRF is that they allow for endogenous switch of the regime. In particular, a big positive shock occurring in recession, through its impact on the threshold variable can determine the switch to expansion, while the opposite effect can be observed for big negative shocks happening in expansions. Therefore the generalized identification is well suited to analyze the sign asymmetry, i.e. the different impact that positive and negative shocks have on the DY index. However, it is worth mentioning that the endogenous switch in regime depends not only on the size of the shock but also on the threshold variable Z. For example, when the economy is in a very deep recession, a cer-

[3] The Generalized variance decomposition is preferred in most of the DY index applications for its invariance to the ordering of variables.

Table 2.3: Global Financial Data symbols

Country/Variable	IP	SPI	PPI
US	USINDPROM	SPXD	WPUSAM
Japan	NDJPNM	TOPXD	WPJPNM
UK	NDGBRM	FTASD	WPGBRM
Germany	NDDEUM	GDAXIPD	WPDEUM
France	NDFRAMN	CACTD	WPFRAM
Italy	NDITAM	BCIID	WPITAM
Spain	NDESPM	SMSID	WPESPM

tain sized positive shock would not push the economy to expansion; in change when the recession is shallow, the same shock would push the economy into the expansion state.

In the generalized framework the shocks are not necessarily orthogonal. As such, in order to validate our results we run a robustness analysis in which we append the Cholesky decomposition to the GIRF in 2.13. The results are qualitatively similar. Global connectedness is always higher in recessions. As expected, the directional connectedness is slightly smaller in magnitude, but consistent with the benchmark results.[4] Figure S8 describes the difference in the global connectedness across regimes with this alternative choice of the shock identification, while Figure S9, Figure S10 and Figure S11 present the correspondent results for each of the three model specifications employed in the baseline analysis. We relegate to the appendix for further details.

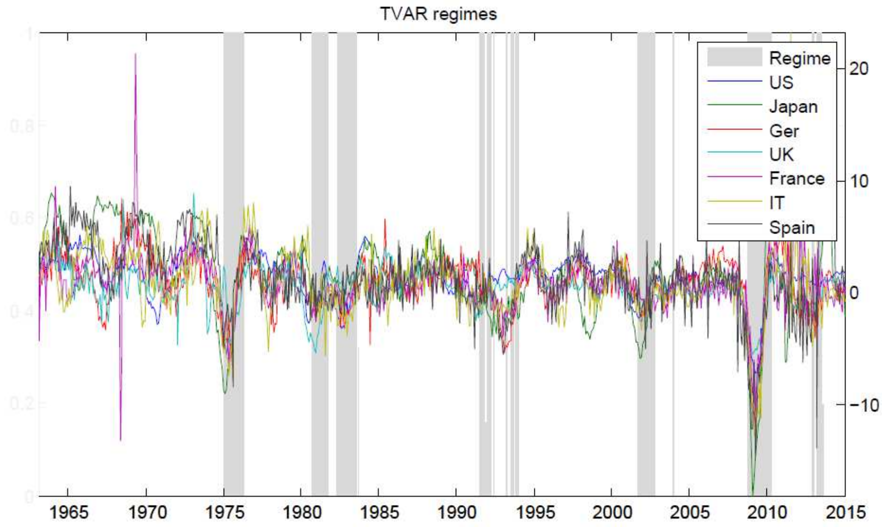
2.4 Data

In this paper we investigate the behaviour of the connectedness index illustrated above in seven advanced economies: USA, Japan, United Kingdom, Germany, France, Italy and Spain[5]. For each country, we use monthly data from February 1963 to January 2015 for seasonally adjusted Industrial production (IP), Stock Price Indexes (SPI) and Producer Price Index (PPI). The IP index comprises the categories of mining, manufacturing, electricity, gas and steam and water; waste management. Similarly the producer Price Index covers the prices of the characteristic products of agriculture, forestry and fishing, mining, quarrying manufacturing and electricity, gas and water supply. All variables are considered in year on year log growth rates and are taken from Global Financial Data database. Table 2.3 reports the Global Financial Data symbols for each variable.

[4] The GIRF are equivalent to a Cholesky strategy in which the shocked variable is always ordered first. In such a framework the standard recursive strategy is a lower bound of the generalized identification.

[5] Initially we focused on G7 countries. Because of the high correlation between industrial production index in USA and Canada we replaced Canada with Spain.

Figure 2.1: Global recessions. The lines represent the monthly IP growth series for each country in the sample. The gray bands identify periods of global recessions estimated by the TVAR model.



2.5 Results

In this section we describe our main results. We start with the benchmark model which features country IP growth rates as endogenous variables. Further to this, in two extensions of the baseline model, we add financial and nominal variables to the benchmark model. The main finding of this analysis is that global connectedness is state-dependent with significantly higher values during recessions. This result is robust across all three different model specifications.

2.5.1 Benchmark model

In the benchmark specification we estimate the TVAR model using IP for the seven countries in the sample as endogenous variables. In this setting, the connectedness index is calculated from two sets of Generalized IRF, one for each regime. The shocks are generic growth surprises, hence we refrain from interpreting the transmission mechanism. We use the variance decomposition obtained with the draws saved after the burn-in period to calculate the connectedness index in each regime[6].

[6]The difference of the two indexes (recession less boom) is treated as a random variable in the Gibbs sampling algorithm. We plot its median over the forecast horizon together with the 68% credibility bands (see Figure S3) and we asses the statistical significance of the results. The choice of the credibility bands follows Sims and Zha (1999). More recent references regarding the inference in VAR models include Inoue and Kilian (2013) and Inoue and Kilian (2016). In the first one the authors suggest a novel way of calculating error bands in a sign identified model estimated with Bayesian methods and the empirical exercise reports 68% high probability bands. In contrast, Inoue and Kilian (2016) take a frequentist perspective and propose to construct confidence sets for structural impulse response functions based on inverting a Wald test statistics. They report both 68% and 95% significance level since this confidence levels correspond to one and two-standard pointwise error bands under normality. However, in an additional check we show that our results hold also with 95 and 99% high probability bands (see Figure S18).

Before showing the results we describe the features of the regimes identified by the TVAR model described by equations 2.1-2.2 . The regimes are introduced in Figure 2.1. The gray area represents the median estimate of 1 - S_t which is equal to 1 when the threshold variable Z_t is below the estimated threshold level (see 2.2). Since the threshold variable is constructed as a weighted mean of the IP growth in the seven countries under analysis, we refer to this regime as the "global recession" regime. The global economy enters in recession during the two oil crises, the early 1990s recession, the dot-com bubble and the 2008 global financial crises.

Next, we present the values of the connectedness index in good and bad times while considering shocks of different size and sign. In Figure 2.2, each bar represents the median of the connectedness index under different shock specifications. The index is higher in recessions and it captures a substantial share of the total variance of the model. External shocks explain from 40% to 50% of the forecast error variance decomposition in downturns and from 30% to 40% in expansions. These results are in line with part of the previous findings claiming that due to globalisation, business cycle has become more synchronized with co-movements in economic activity found to be higher in periods of contraction (Canova at al., 2007; Diebold and Yilmaz, 2013; Klößner Sekkel, 2014). From a theoretical perspective, our findings are also consistent with Perri and Quadrini (2017) who employ a two-country model with occasionally binding financial constraints and show that with endogenous credit shocks a global liquidity shortage induced by pessimistic self-fulfilling expectations can lead to sharp and syncronized contractions in both real and financial variables across countries. They also suggest that with higher financial integration the crises are less frequent but when they occur they have bigger effects and generate high co-movement across economies. In contrast, Stock and Watson (2005) claim that the co-movement in the macroeconomic aggregates dropped during the globalization era while Doyle and Faust (2005) find no evidence of increased synchronization in output growth-rate correlation for the G-7 countries.

However, our analysis goes beyond earlier findings as we also analyze the sign asymmetry of shocks. In this application, the size and sign of shocks matter through their impact on the threshold variable. Hence for small shocks of 1 SD (1st to 4th bar) results are unchanged across different sign specifications of shocks. Figure 2.2 (5th to 12th bar) shows that the sign of big shocks is also relevant for the connectednes; if large positive shocks decrease the connectedness, large negative shocks have the opposite effects, especially if they hit economies in booms. Therefore, big negative shocks drag countries into recession and this explains the higher connectedness generated by big negative shocks.

So far we have presented results regarding total connectedness; however, directional

Figure 2.2: Industrial production connectedness index in recessions and expansions. Shocks of different size and sign are considered.

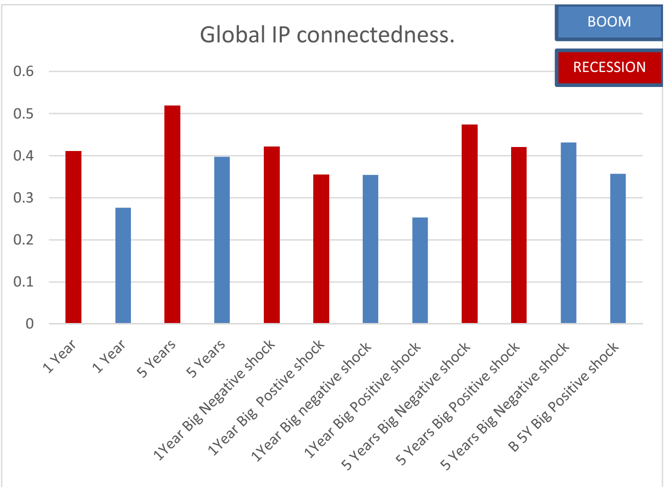
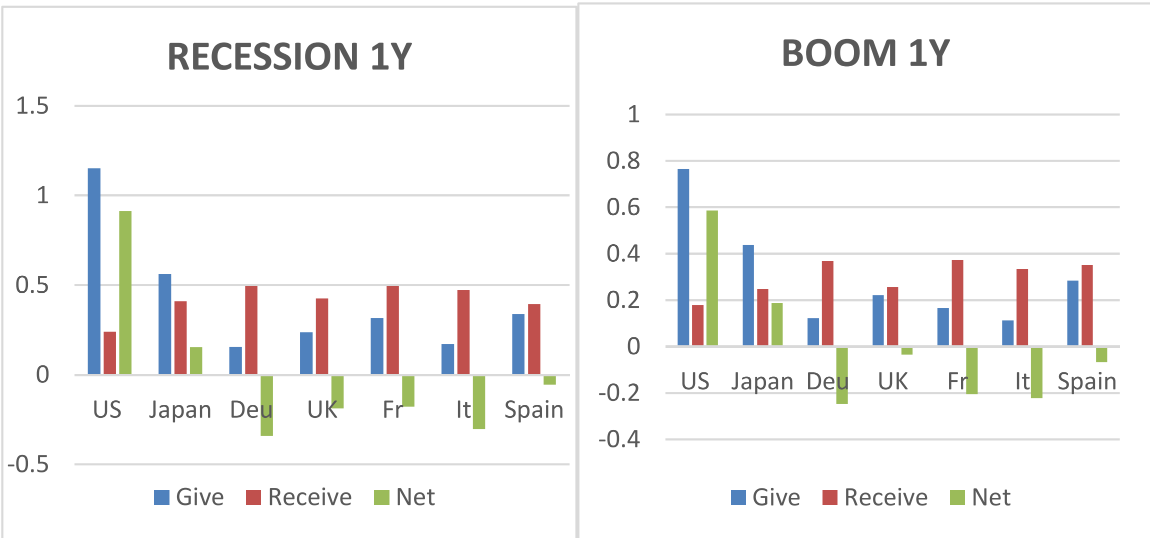


Figure 2.3: Directional results in recession and boom over 1 year forecasting horizon



results bring some very interesting insights as well. In Figure 2.3 we present three sub-indexes of connectedness, including “Connectedness To Others” or “Give”, “Connectedness From Others” or “Receive” and “Net connectedness” or “Net”.

As expected, the US is the most important source of country connectedness with the highest value of “Give” index, followed by Japan. European countries in contrast are net shock recipients independently of the state of the economy. These findings are in agreement with Monfort et al. (2003) who claim that Europe has become more sensible to shocks originating in North-America, while US remains insulated from developments in Europe. The negative values of “Net connectedness “ index for European countries might be explained also by the regional connectedness on top of US spillovers; shocks occurring in Europe might not affect much the US or Japan, but they all have an impact on the other European countries. Even if Germany has been the biggest economy and manufacturing force of Europe, it is also the major shock recipient among the analysed countries. In line with Diebold and Yilmaz (2013), these results point to an important role of the trade channel in the shock transmission[7].

Among European countries, Spain is the main transmitter of business cycle shocks. Analogous findings are provided by Antonakakis et al. (2016). The conclusions are qualitatively similar across business cycle phases, but we obtain higher values for the directional indexes in recessions. Regarding the sign asymmetry, negative shocks originating in the US have higher spillover effects than positive ones, especially if they occur in good times. In the long run the differences in directional connectedness across the states of the economy are negligible (see Figure S13).

In a robustness analysis we have replaced IP indexes with quarterly GDP. The results reported in Figure S12 reinforce the findings obtained in the baseline specification.

2.5.2 Financial and inflation connectedness

Up to now the paper has provided evidence of higher connectedness of real variables in recessions compared to booms. However existing empirical literature attributes an increasingly important role to financial spillovers and several studies suggest that real and financial variables have become more and more interconnected. For example, Chauvet et al. (2015) are concerned with the interactions between financial and real variables and show that financial sector has a significant effect on real economy. Cotter et al., (2017) employ the DY index and analyse the spillovers between real and financial sides of US economy. They find that financial markets are net shock transmitters to the real variables. On the other side, several studies have examined the international co-movement of inflation documenting the fact that movements in inflation rates across advanced economies is highly synchronized (Ciccarelli and Mojon, 2010; Mumtaz et al. 2011; Mumtaz and Surico, 2012; Henriksen, et al., 2013).

So far though, the empirical literature has not investigated the asymmetry of the connectedness in financial and nominal variables across business cycle phases, neither their state-dependent interactions with the real side of the economy. Trying to fill this gap, in this section we propose two additional specifications. Building on Cotter et al. (2017) and Park and Shin (2017), in the first model we mix financial and real variables while in the second one inflation and IP variables are combined[8]. Therefore the final model is a

[7]Germany is the most important exporter of manufacturing goods to France, UK and Italy and second or third to US and Japan and it makes sense for Germany to have a higher connectedness from others.

[8]Incorporating different types of variables in the baseline model has two main advantages. First, it allows for the identification of global recessions and booms, which requires the IP variables. Second, the mix-variables approach facilitates the analysis of real-financial and real-inflation spillovers in addition to the connectedness of financial and inflation variables across business cycle phases.

multi-country multi-variable model featuring 14 endogenous variables.

From a practical perspective, in order to ease the interpretation of the results we rely on Greenwood et al., (2015) and Park and Shin (2017) and we introduce an intermediate level of aggregation based on the type of variable. The aggregation scheme is described in the Appendix S4. The financial variables used in this exercise are the annual log growth rates of the Stock Price Index for each country, while inflation is calculated as the year on year log growth rate in the Producer Price Index.

Figure 2.4 corresponds to the first specification, thus it presents the dynamics of real and financial connectedness over the phases of the business cycle. A clear benefit of the mixed-variables specification is that it allows for the analysis of the composition of the global connectedness index. Specifically, the global index is obtained as the sum of 4 sub-indexes, namely RR, RF, FR, FF, in which RF and FR capture the interactions between real and financial side of the economy[9], while RR and FF show the connectedness in real and financial variables driven by their own shocks (see Appendix S4 for details). As can be seen from Figure 2.4, the introduction of financial variables in the model does not alter the main conclusions obtained in the baseline analysis. Global connectedness is much higher in recessions than in expansions, with negative shocks having a larger impact compared to positive ones. However, we find that the level of overall connectedness is around 10% higher than the one obtained in the benchmark model featuring only real variables. The results also suggest that shocks to financial variables are very important in explaining connectedness across countries.

In addition, from the decomposition of the total index in sub-indexes we learn that real and financial indexes have very different dynamics. Specifically, connectedness among financial indicators generated by shocks to these variables (FF index) explains the bulk of total connectedness and is constant across business cycle, time horizon and different shock specifications. It follows that cross-country connectedness in financial variables is dominated by its own shocks. In contrast, real shocks have a smaller effect on the connectedness of financial variables. One interpretation for this result is that financial shocks are the most powerful exogenous impulse in the system. Indeed, financial shocks have quantitatively large effects on IP connectedness (FR index) with greater values displayed during recessions and in the case of negative shocks. Thus, during crises shocks hitting the financial sector are transmitted to the real variables in a virulent way. The connectedness in real variables generated by its own shocks is relevant but with less variability than expected. These results are unsurprising since financial markets are generally thought to be the leading indicators of economic activity (Abbate et al. 2016; Prieto et al. 2016; Cotter

[9]For example RF capture the financial connectedness generated by generic shocks to real variables.

Figure 2.4: Financial and IP connectedness. R and B at the bottom of each bar stays for recession and boom. The RR, RF, FR and FF in the legend indicate the type of variables, i.e. real and financial.

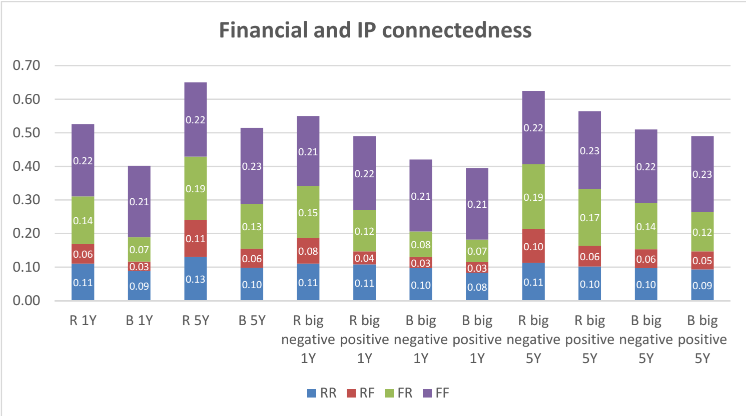
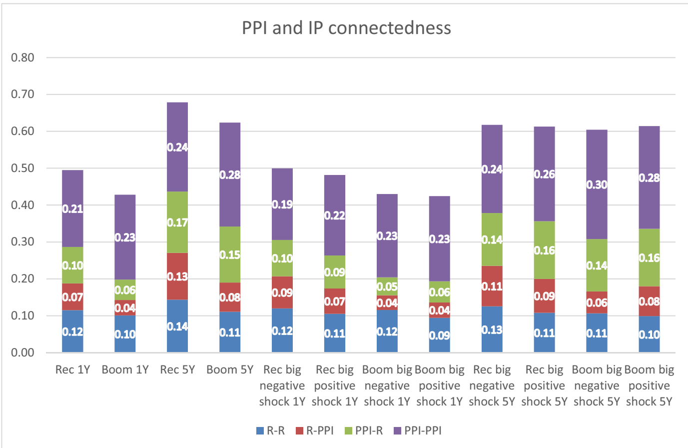


Figure 2.5: Inflation and IP connectedness. R and B at the bottom of each bar correspond to recession and boom.



et al., 2017).

Figure 2.5 presents the results obtained from the model that combines real and nominal variables. Our findings reinforce the hypothesis of a strong co-movement in inflation rates. Rogoff (2006) claims that the increased synchronization in nominal variables across countries could be caused by the fact that global factors drive inflation because global excess capacity has become progressively more relevant than domestic excess capacity in forecasting cyclical domestic inflation. In addition, the results suggest that inflation connectedness (purple bars) captures a substantial share of total connectedness, it is higher than IP connectedness generated by IP shocks (blue bars), and it varies with the state of the economy, with larger values in booms compared to recessions. A mechanism to explain the higher synchronization in nominal variables compared to the real ones has been put forward by Henriksen et al. (2013) and is based on cross-country spillovers from technology shocks which are transmitted into nominal variables through an interaction between Taylor-type rules and domestic nominal bonds; this makes nominal variables depend on expected movements in domestic GDP and the return on domestic capital in all future periods, which are more connected than current GDP because of the cross-country spillovers. In addition, co-movements in inflation exhibit some differences over the forecasting horizon with greater values in the long run. These results are consistent with the long term objectives of monetary policy which seem to be better achieved in tranquil times (higher inflation connectedness in boom). [10] Concerning the indexes capturing the interaction between nominal and real variables, we notice some differences across business cycle phases and forecasting horizon, with higher values in recession and in the long run while the PPI shocks generate more co-movement in IP variables than the other way around (higher green bars than red bars). In this regard, Mumtaz et al. (2011) suggest that external developments are the main driver of the countercyclicality of prices after WWII as a result of increased competition in goods and labor markets as well as of migration. For example if firms can off-shore activities to economies with lower wages, domestic workers have less bargaining power in pushing for higher wages when unemployment is low, leading to a smaller sensitivity of prices to movements in real variables.

2.5.3 Results using IP weights.

The results reported up to now are based on the specification of the threshold variable based on GDP weights since they are available for the whole sample period. However, the significant differences in the share of industry in GDP across countries might raise concerns on the appropriateness of using GDP share weights in defining the threshold variable. In this section we report results obtained using Global IP share as weighting since 1991. Figure 2.6 suggests that the previous findings are little affected by the change in the threshold weights.

2.5.4 Counterfactual analysis

So far this paper has discussed the state-dependent behavior of cross-country connectedness and we have shown that countries tend to be more connected in recessions than in booms. However, not much has been said about the relevance of these results from an economic point of view. In order to shed some light on this, we conclude this section with a counterfactual exercise aiming at obtaining a model-based narrative on the role that synchronisation has played historically. Our results pointed out that shocks originating from the US are the most important source of connectedness across advanced economies; as such, in the context of this paper, an interesting counterfactual would be one where

[10] One of the candidate explanations of international inflation co-movement in the literature is the improvement in the effectiveness of monetary policy across several developed countries in the last decades.

Figure 2.6: Results obtained using IP weights in constructing the threshold variable.

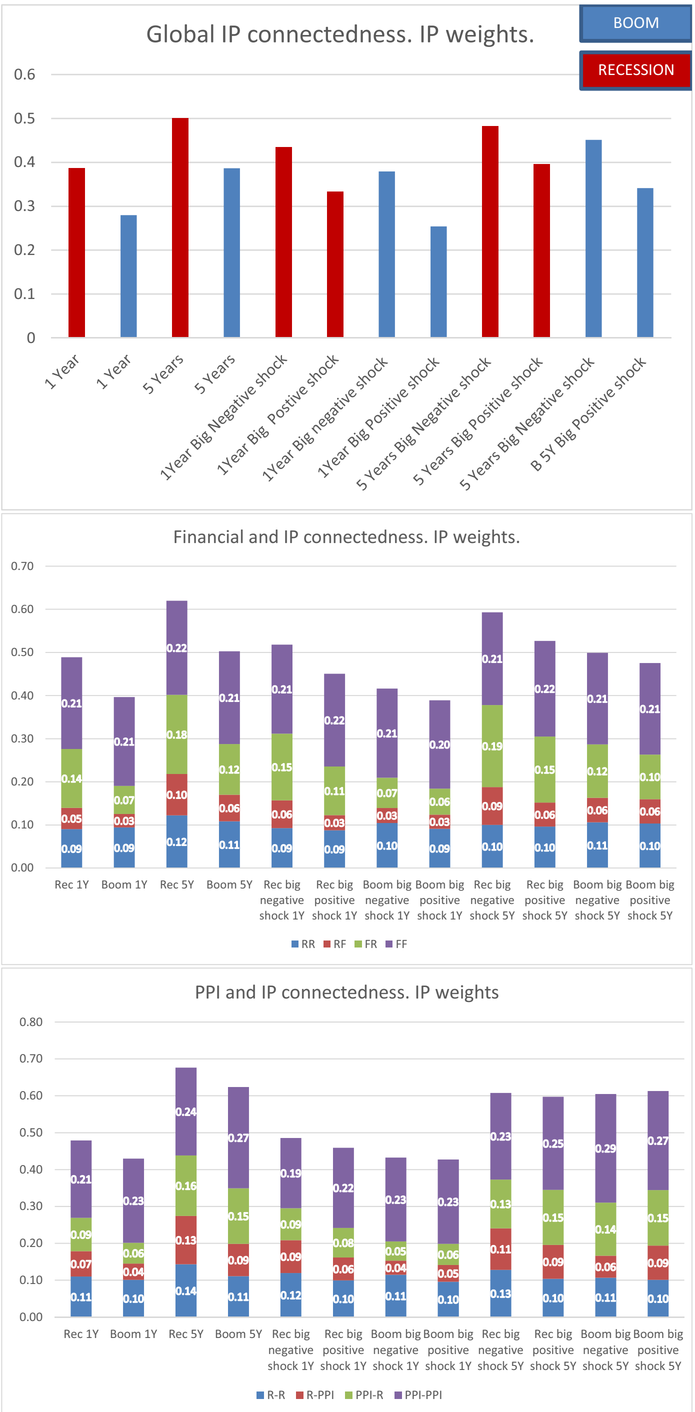
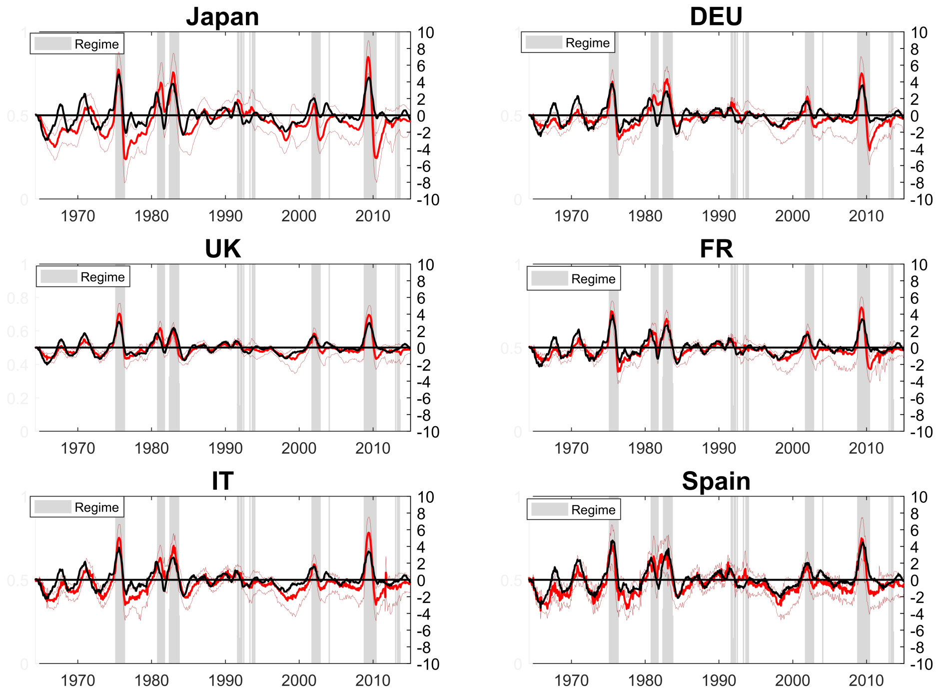


Figure 2.7: Counterfactual scenario. The figure shows the difference between the IP series generated by two models under the counterfactual assumption and the actual data. The red lines are the median obtained from the Threshold VAR model and the brown lines indicate the correspondent 68% confidence bands. The black lines are generated from a linear VAR model. The gray bands identify the estimated recessions by the Threshold VAR model.



US related shocks are removed. The methodology which we employ to perform this is the following: for each saved draw of the estimated parameters we reconstruct the structural shocks using the Cholesky decomposition with the US ordered first[11]; we then set disturbances coming from the US to zero and use these modified shocks to simulate the data in a counter-factual scenario. The new series can be interpreted as the realization of the data that would have been observed had the connectedness been decreased by switching off shocks in the US. As we do not change the values of the parameters, the Lucas' critique is not important in this exercise (Benati, 2010).

Results from this exercise are presented in Figure 2.7. The benchmark model (red line) is compared to a linear VAR (black line). For each model and country (except for the US) we plot the difference between IP series generated by the two models under the counterfactual assumptions and the actual data. It can be noticed that recessions are associated with positive IP values; specifically, if countries were completely immune to US disturbances, their IP growth in downturn periods would be more than 4% higher. The opposite effect is observed in expansions when US related shocks bring a positive

[11]By ordering US first we assume that US IP is the most exogenous variable in the system which in the current context in is not a very restrictive assumption

contribution to growth in IP outside the US itself. We have qualitatively similar effects for the no-threshold model but with a much smaller magnitude (marked by the difference between the red and the black line). These findings are in line with our expectations given the higher connectedness in recessions depicted by the threshold model. The linear model which does not account for state-dependency, underestimates the relevance of US shocks. Summing up, Figure 2.7 shows that the connectedness is important from an economic point of view and accounting for its state-dependent behaviour is essential in order to effectively capture its effects on the real economic activity.

2.6 Robustness analysis

There are several concerns raised by our analysis and we try to address them performing additional robustness checks. More details on the sensitivity tests discussed in this section can be found in the appendix to the paper. As a first check, we re-estimate the model using the Smooth Transition VAR instead of the TVAR and we show that results are robust to a less restrictive specification of the transition function. Since in the generalized identification shocks are not necessarily uncorrelated, in order to validate our findings we replicate the empirical exercise using the Cholesky decomposition to identify the shocks. Results are qualitatively similar with slightly smaller magnitude than in the generalized framework.

Moreover, the directional results in section 5.1 have shown the centrality of US shocks as drivers of the global connectedness in both recessions and expansions. However, US share dominates the threshold variable and this might raise questions on the implications of the US dominance in the threshold variable on the results showing the importance of US as a shock transmitter. In order to check whether the US dominance in the threshold variable has an influence on the directional results we run the following robustness analysis: we identify the states of the economy solely based on Germany and then we estimate the directional results and the importance of German shocks to US and US shocks to Germany. Figure S19 shows that directional results are little affected by this adjustment in the threshold variable while Table S4 reports a low influence of German shocks on US IP and a high relevance of US shocks in explaining the forecast error variance decomposition of the German IP independently of the way the threshold variable is constructed.

Additionally, we check the sensitivity of our estimates to the size of big shocks and to the prior tightness. Furthermore we re-run the model replacing the real activity and inflation variables from the baseline specification, i.e IP and PPI, with GDP and respectively with the Consumer Price Index. All these tests further support the robustness of our conclusions.

2.7 Summary

We estimated the connectedness in IP for seven advanced economies; using a nonlinear setting we focused on analysing its asymmetry over the business cycle. We then extended our analysis and we included financial and inflation variables in order to get a deeper understanding about the composition of the connectedness index. The methodology employed consisted in the estimation of a Threshold VAR model via Bayesian methods. The choice of the econometric model was validated by performing a model selection and a sensitivity analysis.

Our findings suggest that during recession countries tend to be more connected and the estimated difference is large and statistically significant. In addition, negative shocks are found to have higher impact on the connectedness index compared to their positive counterparts. We also show that financial and inflation shocks are important determinants of global connectedness, and that connectedness indexes for these variables have a different behaviour compared to the real activity ones. Specifically, both inflation and financial connectedness are large and less state-dependent than the IP index. Financial shocks are important drivers of the cross-country connectedness in real variables, especially during recessions, while the opposite effect is not verified. These results reinforce the idea that movements in financial markets could lead economic activity. Cross-country inflation connectedness is higher in the long run, which is consistent with the shared long term objectives of monetary policy makers. Among the analysed countries, the US and Japan are the main "shock givers" while European countries tend to be more shock "takers". A counterfactual exercise illustrates how relevant connectedness is from an economic point of view and the necessity to account for its state-dependent behaviour.

Moreover, a better understanding of the cross-country spillovers it is important also from the policy perspective. That said, the finding that connectedness is asymmetric across the business cycle suggests that standard linear models might not be appropriate for the policy analyses of cross-country spillover. Finally, policymakers should learn that not all spillovers are the same as their relevance depends on the nature and the origin of the shock. In general, shocks originated in the US matter from a global perspective more than shocks originating in other regions.

There are several issues that this paper has left unanswered, including for example the causes of increased connectedness during recession and the main channels of transmission of shocks across borders. We intend to consider these questions in future work.

Chapter 3

The contributions of fiscal and monetary policy since the global financial crisis.

3.1 Introduction [1 2]

In the aftermath of the 2008 global financial crisis, the design of an effective policy response became the main priority around the world. Spurred by policy commitments at the 2009 G20 London Summit, central bank and government interventions addressed macroeconomic instability and slumping demand with substantial policy support including (standard and non-standard) monetary policies and fiscal stimulus (Figure 3.1). Since then, debate has raged over the efficacy, efficiency and appropriateness of the response. To name but a few, the topics have covered the role of the mix between fiscal and monetary policies (Krugman, 2015); the benefits of unconventional monetary policies (Borio and Zabai, 2016); and the long-term consequences of the policy response (IMF, 2017a).

In recent years, however, priorities have gradually changed. Growth in global activity has revived over the past two years as the cyclical upswing gathers strength (IMF, 2017b). Spare capacity across many economies has narrowed substantially and policymakers have turned their attention towards policy normalisation. Albeit gradually, the 'long decade' of policy accommodation is apparently drawing to a close. Yet, as policymakers edge at different speeds towards the stages of policy withdrawal, it is crucial for them and us to understand the extent to which the global economy is still dependent on policy support.

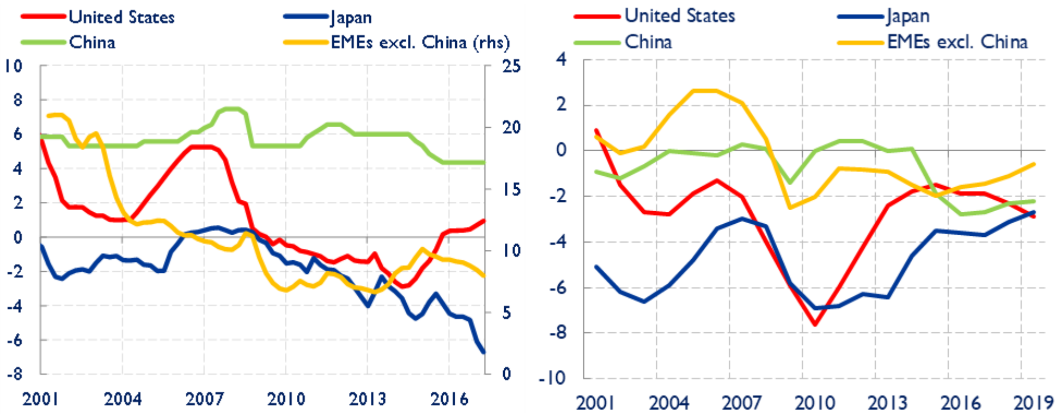
[1] This chapter is coauthored with Ursel Baumann and David Lodge, ECB. The paper is available in the ECB working papers series as: Baumann, U., Lodge, D. and Miescu, M.S., 2019. Global growth on life support? The contributions of fiscal and monetary policy since the global financial crisis (No. 2248).

[2] The content of this chapter should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB.

Figure 3.1: Policy intervention. Stylized facts.

(a) Key policy interest rates (percent)

(b) Cyclically adjusted primary balances (percent of GDP)



Too quick a withdrawal could force the economy into a sharp reversal; too slow could store up future troubles. This paper aims to understand the role of policies in supporting activity over the past decade.

Up to now, very little attention has been paid to analysing the differences (or similarities) in the role played by policy support in advanced and emerging economies. This is an important topic for research and policymakers. The global financial crisis affected advanced and emerging economies differently and required tailored policy responses. Facing a severe turmoil in their financial markets many advanced economies confronted a deep and long-lasting slowdown in activity. Some faced the challenges of operating monetary policy at the zero lower bound; in subsequent years, others were confronted with market-driven or politically necessitated fiscal consolidation. By contrast, partly because emerging market economies rebounded more quickly in the immediate aftermath of the global recession, the policy response differed (ECB, 2016). A deeper understanding of how policy contributed across both groups would benefit both policymakers and academics.

This paper aims to contribute to this growing area of research by exploring the heterogeneity in policy effects across groups of countries. Using structural panel VARs in the spirit of Jarocinski (2010) we examine the joint role of fiscal and monetary policies in shaping global growth since the global financial crisis in both advanced and emerging economies. As Caldara and Kamps (2008) note, vector autoregressive (VAR) models have become a key econometric tool to assess the effects of monetary and fiscal policy shocks. Our paper is therefore related to the wide literature on the identification of monetary and fiscal policy shocks, which are well summarized in Ramey (2016).

The contribution of our work to the literature is fourfold. First, we estimate and compare the effects of policy across a range of advanced and emerging market economies

(EMEs). We estimate structural panel VARs for a set of large advanced and emerging economies (US, euro area, UK, Japan, Brazil, China, India and Russia), which together represent over half of global GDP (at purchasing power parity).

While the literature on the effects of either monetary or fiscal policy in individual countries is vast (see Ramey, 2016), fewer papers have provided comparisons of policy transmission across countries. For monetary policy, Jarocinski (2010) compares the responses of monetary policy shocks in the east and west of Europe, while Mandler et al. (2016) examine the heterogeneity across countries within the European Monetary Union. There has been more limited investigation into the effects of monetary policy in EMEs. Mallik and Sousa (2012) analyze responses in large emerging markets. Perez-Forero (2015) compares the transmission of monetary policy shocks in Latin America using a hierarchical panel VAR. On the fiscal side, Burriel et al. (2009) compare the responses of the United States and euro area to fiscal shocks. Ilzetzki et al. (2013) find that the output effect of an increase in government consumption is larger in industrial than in developing countries.

Second, we look at effects of fiscal and monetary policy in combination. Particularly for studies using VARs, the literature has tended to examine fiscal and monetary policies in isolation. The Christiano, Eichenbaum and Evans (1999), Handbook of Macroeconomics chapter, for example, concentrates on the identification of monetary policy shocks, while Ramey (2016) devotes separate sub-sections to the topics of fiscal and monetary shock identification. Other leading types of externally identified monetary policy shocks such as the Romer and Romer (2004) narrative method, or the high frequency identification of Gertler and Karadi (2015) also focus narrowly on the question of understanding monetary policy effects. The picture is similar for fiscal policy: for example, Blanchard and Perotti (2002) focus only on the role of government spending and tax shocks. In examining the role of fiscal shocks in the United States, Caldara and Kamps (2008) include interest rate variables within the VAR specification but report only the economic responses to government spending and tax shocks under a variety of identification approaches. The policy response to the global crisis required monetary and fiscal action in an effort to boost the demand. Separating monetary and fiscal policy overlooks the potential policy interactions. Our study aims to understand the combined role of both forms of policy.

Third, to discern the effect of fiscal and monetary policy on GDP growth we use counterfactual scenarios in a structural setting. We compare model forecasts conditioned on actual policy developments with forecasts conditioned on a counterfactual policy path. We judge the impact of policy on activity by assessing the difference in projected paths for GDP growth in the two scenarios across our sample of countries. In effect, we ask: what would have happened to the economy without the observed policy easing? Kapetanios et al. (2012) and Lenza et al. (2010) conduct similar exercises in examining the role of monetary policy in the UK and the US, euro area and UK respectively. However, both approaches rely on the reduced-form model to inform the conditional scenarios used. Our counterfactual exercise takes a different approach by relying on the structural form of the model, attributing outcomes for policy specifically to the relevant monetary and fiscal shocks identified in our model. A particular advantage of our approach, in using structural conditional forecasts, is that it captures the variability in the GDP response to shocks (through identification of shocks).

Finally, we study the interaction and interdependency of the two branches of macroeconomic policy over the past decade. A number of recent papers (Bianchi and Ilut, 2017; Bianchi and Melosi, 2017; Corsetti et al, 2016; Jarociński and Maćkowiak, 2018) emphasize the relevance of analyzing the policy mix for economic outcomes. Our contribution is to use counterfactual scenarios to understand the role of different policies in the recent period, asking the questions: how might monetary policy have behaved if fiscal policy had been conducted differently?; and how strong would fiscal support have needed to be, had monetary policy been less accommodative? In asking these questions we aim to provide an understanding of the interdependencies of policies and the effect on activity over the past decade.

In analysing monetary and fiscal transmission across countries, we employ an econometric technique that allows us to analyze countries jointly within panel models. We estimate separate models for the two groups of advanced and emerging economies and, following Jarocinski (2010), use Bayesian estimation. The approach employs so-called hierarchical priors which have the assumption that parameters are drawn from a common mean across each group, but allow for heterogeneity in the coefficients via the hierarchical prior which is endogenously determined and governs the degree of heterogeneity across individuals. In doing so, it makes efficient use of available data. In particular, for EMEs for which time series are relatively short, this is a considerable advantage. A further benefit is that the approach can reveal heterogeneity in the propagation mechanism within each group and also between different policy tools.

Our main results can be summarised thus. Consistent with previous studies we find that fiscal multipliers are mostly higher in advanced economies compared to EMEs. We also show that in the last two decades AEs have conducted an active monetary policy which has tended to offset the effects of expansionary government spending measures. In contrast we see less strong reaction of monetary policy to fiscal policy shocks in EMEs. The response of GDP in EMEs to monetary policy shocks is also broadly in line with the literature, with activity in emerging economies affected somewhat more strongly than in advanced economies following a contractionary monetary shock. Moreover, we find that the GDP response to fiscal shocks is more heterogeneous (between and within groups) than the response of GDP to monetary policy shocks.

Turning to the conditional scenarios, we find that GDP growth in our sample of countries benefited from substantial policy support during the global financial crisis but policy tightened thereafter, particularly as fiscal consolidation in advanced economies acted as a significant drag on the subsequent global recovery. Since 2016, policies have become more supportive overall. That is consistent with the observed improvement in global activity in that period although it also emphasizes that the global recovery has been reliant on policy support and underscores the need for a gradual and calibrated withdrawal of policy accommodation. In addition we show that the role of policy has differed across countries. Specifically, in advanced economies, highly accommodative monetary policy has been counteracted by strong fiscal consolidation since 2011. By contrast, in EMEs, monetary policy has been less accommodative since the global recession.

Finally, our results emphasise an important interdependence between monetary and fiscal policies. Counterfactual scenarios undertaken for the United States suggest that without the fiscal policy reaction, monetary policy would have needed to be significantly more accommodative during the financial crisis. Thereafter, however fiscal consolidation has required monetary policy accommodation for longer. Indeed, without the fiscal consolidation undertaken after 2011, interest rates could have risen above the zero lower bound already in 2013. This also implies that without monetary policy support the strong fiscal consolidation would not have been possible without causing a significant slowdown in US growth. .

The paper is organized as follows. Section 2 introduces the methodology and the data. Section 3 reports the results. Additional robustness checks are conducted in section 4 while section 5 concludes.

3.2 Methodology and data

This section introduces the empirical model, the data and the identification strategy.

3.2.1 Empirical model and the data

We estimated the following reduced form VAR model for country c:

$$Y_{tci} = \sum_{p=1}^{l} Y_{t-p,ci} \beta_{ci}^{p} + Z_t \Phi_t + u_{tci} \tag{3.1}$$

$$u_{tci} \sim N(0, \Omega_{ci}) \tag{3.2}$$

where i denotes the group of countries (advanced vs. emerging economies), c= 1,2,...M is the number of countries in each group and t=1,2,...T is the sample size. For the estimation purpose we rely on a hierarchical panel VAR framework in the spirit of Jarocinski (2010); a separate model is estimated for each group using Bayesian Methods.

Y_c is a $T \times 5$ matrix of endogenous variables for country c and includes a proxy for government spending, GDP, inflation, tax and a monetary policy instrument. Government spending measures real government consumption and investment – i.e it excludes the elements such as transfers (e.g. unemployment benefits) which would depend on the business cycle; we also exclude interest payments.[3] Government revenues are measured as taxes less transfers and (where possible) interest payments. The monetary policy instrument is the policy interest rate.[4] For the advanced economies we address the additional restrictions caused by the zero lower bound (ZLB) using a shadow interest rate for the period from the end of 2008 (Wu and Xia, 2014 and Lemke et al. 2017). One concern that might arise is that the ZLB regime could imply a change in the model parameters. However, several studies that analyze the effects of unconventional monetary policy seem to suggest that model parameters have remained broadly stable despite the introduction of unconventional measures (Gambacorta et al. 2014; Wu and Xia, 2016; Hachula et al. 2016).

To account for the world developments, we add Z_t, a $T \times 5$ matrix of exogenous variables common to all countries containing the VIX index of equity volatility, world GDP, non-oil commodity prices, oil prices and a constant. It is worth noting that the exogenous variables in Z enter the model at time t while all the other regressors represented by a $T \times 5 \times l$ matrix are lagged values of the endogenous variables Y_c. All variables are transformed in year on year growth rates, with the exception of the monetary policy instrument. The data we use is at quarterly frequency and runs from 1998 to 2016 for AEs (US, euro area, Japan and UK) and from 2000 to 2016 for EMEs (China, Brazil, India, Russia). The lag length l is set to 5 for AEs and 6 for EMEs [5]. We relegate to the Appendix a detailed description of the data.

[3] For EMEs group, due to the lack of data on government investment we rely on government consumption to proxy the government spending.

[4] For the EMEs group, where the conduct of monetary policy has changed over time we add also the monetary aggregate M2. This helps alleviate the price puzzle. A sensitivity analysis shows that this adjustment has a rather limited impact on GDP response to policy shocks.

[5] Both the marginal Likelihood and Deviance Information Criteria (see Table S6) estimated separately for each country prefer models with a number of lags greater than 4. We adopted 6 lags for EMEs since it alleviates the price puzzle. For AEs the model with both 5 and 6 lags provides IRFs with correct sign and similar magnitude but in the model with 6 lags GDP response to monetary policy shock display some persistence which might have undesired effects on the counterfactual scenario. As such for AEs we prefer a model with 5 lags. The sensitivity section addresses the robustness of results to the lag length.

A key feature of this model is that it allows the β coefficients to vary across individual countries as opposed to the standard pooled estimator which ignores cross section heterogeneity. The unit specific coefficients are obtained by imposing a hierarchical structure to the model. Specifically, it is assumed that the prior distribution for the VAR coefficients β_c is defined as follows:

$$p(\beta_{ci} \mid \bar{\beta}_i, \lambda) \sim N(\bar{\beta}_i, \lambda \varOmega_i) \tag{3.3}$$

where $\bar{\beta}_i$ are cross sectional average coefficients updated during the sampling procedure. $\varOmega_i$ is a Minnesota type variance which reflects the scale of the variables and adjusts for the relative size of coefficient[6]. The crucial parameter in this setting is λ which controls the degree of heterogeneity in the model. As $\lambda \to \infty$ the coefficients collapse to the country specific VAR values while for $\lambda = 0$ the model is equivalent to the pooled estimator. Ideally, λ should reflect a good balance between individual and pooled estimates. In a standard Bayesian framework $\bar{\beta}_i$ and λ are calibrated parameters while in the current context they are treated as random variables and have their own distribution.

In brief, equation 3.3reveals the prior knowledge that country coefficients are assumed to be drawn from a common distribution centered around the cross sectional mean but are allowed to deviate from this mean at a higher or lower degree dictated by the value of the endogenously determined parameter λ which is common across units. Therefore, the posterior of β_c is a weighted average of the country OLS estimates and the prior mean defined in 3.3.

The hierarchical structure of the model offers two key advantages that are relevant to our study. First the group specific average impulse response function can be computed using the mean model coefficients $\bar{\beta}_i$ to obtain the estimates. This allows the comparison of the GDP response to policy shocks in advanced versus emerging economies as a group. Moreover, $\bar{\beta}_i$ contains information from the whole panel (and not only one country time-series) and is updated during the sampling procedure; these features are likely to improve the estimation precision. In addition, the hierarchical prior tends to shrink the country specific coefficients towards the common mean leading to a more efficient use of the data and more precise estimates of the unit specific coefficients.

3.2.2 Priors

Following the approach suggested in Dieppe et al. (2017), standard diffuse priors are assumed for $\bar{\beta}_i$ and $\varSigma_{ci}$ while Ω_{ci} is designed in a Minnesota type fashion. Regarding λ, a

[6]As per Litterman 1986, what matters for the size of a coefficient is the relative size of unexpected change in the variable.

traditional choice for the prior distribution is an inverse Gamma distribution with shape parameter $s_0/2$ and scale $v_0/2$. Jarocinski (2010) and Gelman (2006) show that results can be sensitive to the choice of the values for s_0 and v_0. As such, they suggest the use of a uniform prior with s_0 = -1 and $v_0 = 0$ for models where the number of units is greater than 5; or to make the prior weakly informative by using low values for s_0 and v_0 (less than 0.001) which is the strategy adopted in this paper. A sensitivity analysis shows that results are little affected by the use of a uniform prior for λ instead.

3.2.3 Gibbs sampler

We rely on a Gibbs sampler to draw from the marginal posterior of the parameters. The algorithm is based on Jarocinski (2010) and Dieppe et al. (2017) and it draws from the following conditional posterior distributions:

- At iteration i draw $\bar{\beta}^i$ from a multivariate normal distribution:

$N(\beta_m^{i-1}, \mathrm{N}^{-1}\Sigma_b^i)$ with:

$\beta_m^i = \mathrm{N}^{-1}\sum_{c=1}^{N} \beta_c^{i-1}$

$\Sigma_b^i = \left(\lambda^i \otimes I_q\right) \Omega$ where q is the number of coefficients to be estimated for each unit.

- At iteration i, draw λ^i from an inverse Gamma distribution :

$\lambda^i \sim \mathrm{IG}(\frac{\bar{s}}{2}, \frac{\bar{v}}{2})$ with:

$\bar{s} = \mathrm{h} + s_0$ where h is the number of coefficients to be estimated for all units.

$\bar{v} = v_0 + \sum_{c=1}^{N}\left\{\left(\beta_c^{i-1} - \bar{\beta}^i\right)' \left(\Sigma_c^{-1}\right) \left(\beta_c^{i-1} - \bar{\beta}^i\right)\right\}$

Draw $\Sigma_b^i = \left(\lambda^i \otimes I_q\right) \Omega$

- At iteration i, draw β_c^i for each country c from a multivariate normal distribution:

$\beta_c^i \sim N\left(M, V\right)$ with:

$M = \mathrm{V}\left[\left(\left(\Sigma_c^{i-1}\right)^{-1}\right) y_i + \left(\Sigma_b^i\right)^{-1} \bar{\beta}^i\right]$

$V = \left[\left(\Sigma_c^{i-1}\right)^{-1} \otimes X_i' X_i + \left(\Sigma_b^i\right)^{-1}\right]^{-1}$

- At iteration i, draw Σ_c^i for each country c from the inverse Wishart distribution:

$\Sigma_c^i \sim IW(S_c, T)$ with:

$S_c = \left(Y_c - X_c\beta_c^i\right)' \left(Y_c - X_c\beta_c^i\right)$

We use 15000 replications as burn in sample and we save 10000 draws for inference, discarding 99 draws for each one saved draw. [7]

3.2.4 Identification strategy

We base our empirical results on the identification of two structural shocks, namely a government spending shock and a monetary policy shock. The identification strategy follows Blanchard and Perotti (2002) and Caldara and Kamps (2008) and it relies on the recursive identification approach which implies timing restrictions on the contemporaneous impact across variables. The simplicity of this approach is particularly attractive for our analysis since it is easily applicable to both advanced and emerging countries.

The variables enter the model in the following order: government spending, GDP, inflation, tax and the monetary policy instrument. As such, in line with Blanchard and Perotti (2002) it is assumed that government spending decisions are not affected contemporaneously by domestic business cycle developments[8]; therefore reduced form innovations to the first equation coincide with our identified government spending shock. Turning to the monetary policy shocks, to achieve identification we order the monetary policy instrument last and we allow for a contemporaneous reaction of the central bank to fluctuations in the other variables; this choice can be justified on the grounds of a central bank following a Taylor rule in determining the interest rate. Although we control for developments in government revenues, we do not aim at identifying a tax shock. If scholars seem to agree on the exogeneity of the government spending decisions, there is less consensus on whether the tax variable should be ordered before or after the GDP, making the identification of such shock problematic in a recursive framework.

3.3 Results

3.3.1 Model evaluation

To assess the reliability of the estimated panel model, we first consider the model properties. The focus is on the response of GDP growth to innovations in both fiscal and monetary policy variables. We report the fiscal multipliers from both the mean model and the individual country estimates while for the monetary policy we show the mean model IRFs in the main text and the country results in the Appendix (Figure S24). The mean model results allow for the comparison of the IRFs in the two groups of countries, while the single

[7]The estimation is conducted using a modified version of the BEAR toolbox of Dieppe et al. (2017) which accomodates for mean model results estimation and convergence diagnostic test using inefficiency factors.

[8]We do, however, control for the contemporaneous developments at world level through the exogenous variables.

unit estimates tell us something more on the heterogeneity within group of GDP response to policy shocks.

For government spending we convert the impulse response functions into fiscal multipliers to be able to compare them to the literature. Fiscal multipliers measure the average change in real GDP from one unit (measured in national currency) increase in government spending. Specifically, we follow Blanchard and Perotti (2002) and we define multipliers as the ratio of the output response at a particular horizon to the impact effect of the shock on the government spending. However, different countries reach the peak response at different horizons, therefore in order to obtain comparable results across countries we consider the average GDP response over the first three years. Since data is in growth rates, we first convert the growth rates impulse responses to log-levels IRFs; we then calculate multipliers by multiplying the log-level IRFs by the average ratio of government spending over the sample period. Table 3.1 reports the fiscal multipliers, averaged over the first three years, derived from the IRFs.

The mean model results suggest that fiscal multipliers are higher in AEs compared to EMEs. This finding is consistent with previous studies such as Ilzetzki et al. 2013 and Kraay, 2012 who suggest that the degree of development is a critical determinant of the size of the fiscal multiplier. They show that in developing countries, the response of output to government consumption is often negative on impact and not statistically different from zero.

Regarding the country specific estimates, the government spending multipliers have the expected sign, though differing across countries. In the United States, the spending multiplier is 1.3, in line with findings from the literature. For example, Blanchard and Perotti (2002) report a US spending multiplier in the range 0.9 and 1.3, while Ramey (2011a and 2011b) points to a value between 0.6 and 1.2. In Japan, the government spending multiplier is within the ranges reported by Auerbach and Gorodnichenko (2014). The government spending multiplier for the euro area is found to be quite small[9]. In comparison, estimates of fiscal multipliers provided by Kilponen et al (2015) derived from a large number of simulated structural models suggest a spending multiplier in the euro area close to, but below 1. Turning to the United Kingdom, our spending multiplier is higher that the findings of Glocker et al (2017) who report an average (two-year cumulative) government spending multiplier of 0.4, with, however, a significant variation over time.

The literature provides fewer insights on fiscal multipliers in EMEs. The limited empirical literature suggests that fiscal multipliers in EMEs are smaller than in advanced

[9]The low multiplier for euro area is driven by the initial (counterintuitive) negative response of GDP to a spending shock.

Table 3.1: Government spending multipliers in the first three years (average)

US	Japan	UK	EA	AEs	China	Brasil	India	Russia	EMEs
1.3	1.1	0.8	0.4	0.8	0.4	1.2	0.1	0.2	0.2

economies and often are not significant or even negative on impact (Ilzetzki et al. 2013, Kraay, 2012). This finding is confirmed also by our results with the exception of Brazil where the spending multiplier is 1.2. One potential explanation for this finding is that Brazil's economy is relatively closed, which tends to magnify the effectiveness of its fiscal policy. Finally, for China, it is worth noting that our measures may miss important aspects of China's fiscal policy. In particular, data do not allow us to capture off-balance sheet spending by local governments which was a very important component of government spending after the global financial crisis.

Turning to the response of GDP growth to monetary policy shocks, the impulse responses for monetary policy are also broadly in line with the literature. Figure 3.2 shows the mean model IRFs for advanced and emerging countries to a 100 basis points increase in the monetary policy interest rate in each country[10]. The contractionary measure has the expected negative effect on GDP growth for all countries. In advanced economies, the peak impact is reached after around 4 quarters, but the effect exhibits some persistence in the first three years. In emerging economies, the peak impact is slightly larger than for advanced economies, but the response is less persistent. Note, however, that our model may not fully capture monetary policies in all EMEs. For example, during the sample period China used a combination of quantity and price tools to enact monetary policy. In particular, the use of window guidance to bolster credit growth following the global financial crisis, would not be captured.

Contrary to some of the literature for small-scale VARs (see Ramey, 2016), we do not find evidence of a 'price puzzle' for advanced economies, as the response of inflation to a monetary policy shock is negative (see Figure S22 in the Appendix). Overall, this provides some comfort that our monetary policy shocks are correctly identified in our VAR. By contrast, for EMEs, there is evidence of a mild, short-lived price puzzle which sees the inflation rise temporarily after a contractionary monetary policy shock.

It is worth noting that GDP response to fiscal shocks displays more heterogeneity (between and within group) compared to the GDP response to monetary policy shocks[11]. Regarding the monetary policy finding, our results are in line with Jarocinski (2010) and Mojon and Peersman (2001) who show that the effects of monetary policy tend to be

[10]The country specific IRFs for monetary policy are similar to the mean model estimates and are not reported in the main text for ease of exposition. They are available in the Technical Appendix.

[11]We refer to heterogeneity of one policy relative to the other since the parameter λ governing the model heterogeneity is common across units of the same group

even across groups with substantial structural differences. In contrast, other studies such as Cecchetti (1999) and Mihov (2001) find asymmetries in monetary transmission among countries.

On the other side, the variability of fiscal multipliers is not new in the literature. Several studies suggest that fiscal multipliers depend on the economic conditions or on the specific sample analyzed. In particular, Ilzetzki et al. (2013) claim that fiscal multipliers depend on the degree of openness of a country, on the level of debt, the exchange rate regime and on the level of development. Corsetti et al. (2012) highlight important differences in the transmission of spending shocks across countries conditional on the exchange rate regime, the health of public finances and the occurrence of financial crisis. They find higher multipliers during financial crises and in countries with fixed exchange rate regimes, while the weakness of public finances is shown to have a negative impact on spending multipliers. Nickel and Tudyka (2014) focusing on a sample of 17 European countries show that spending multipliers vary considerably with the debt-to-GDP ratios, and can even turn negative at higher levels of debt. Gechert and Rannenberg (2014) reveal increasingly smaller effects of fiscal shocks as the economy is further above its potential (as fiscal measures tend, in these circumstances, to crowd-out rather than crowd-in the private sector). Whalen and Reichling (2015) distinguish specific multiplier ranges for when the economy has an active monetary policy. They point out that: (i) multiplier values are lower under more active monetary policy, which offsets the effects of the fiscal policy measures, stabilising the economy; and that (ii) more credible and/or longer lasting measures usually imply greater effect on output. Coenen et al. (2012) corroborate some of these findings in a structural model with an accommodative monetary policy. Finally, studies focusing on non-linearities such as Auerbach and Gorodnichenko (2012a) and Mumtaz and Sunder-Plassmann (2017) report higher multipliers in recession compared to boom.

3.3.2 Conditional forecasts to evaluate the role of policy support

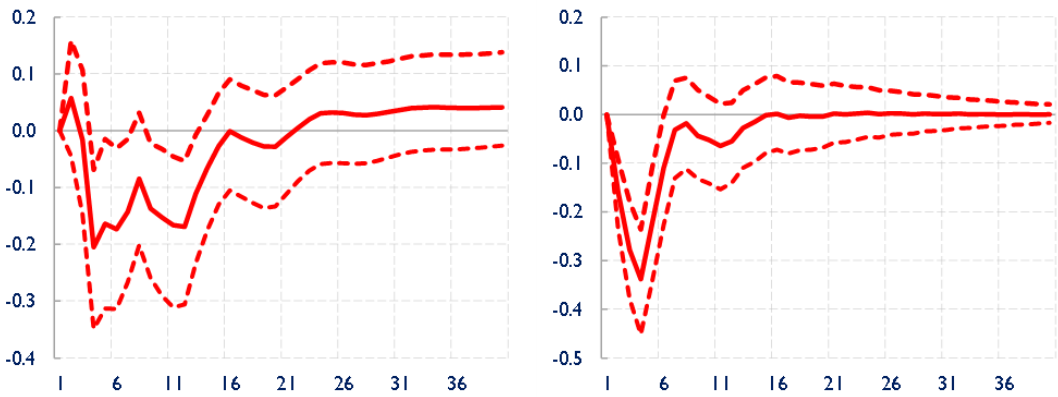
To discern the effect of fiscal and monetary policy on GDP growth, we compare model forecasts conditioned on actual policy developments with forecasts conditioned on a counterfactual policy path. The exercise consists of construction of conditional forecast for GDP growth under two counterfactual scenarios: an actual policy scenario and a counterfactual policy scenario:

1. Under the *actual policy* scenario we produce a path for GDP conditional on the actual realizations of policy variables.

2. In the *counterfactual policy* scenario, the actual values of the policy variables are

Figure 3.2: Impulse responses to monetary policy shocks. Mean model results. Response of year-on-year GDP growth to a 1pp increase in the monetary policy interest rate

(a) Advanced economies (b) Emerging economies



replaced by their sample averages over the estimation period.

To assess the contributions of policy to economic developments, we then compare the median outcomes of the two scenarios – i.e. we subtract the conditional path for GDP growth in the *actual policy scenario* from the conditional path in the *counterfactual policy* scenario.

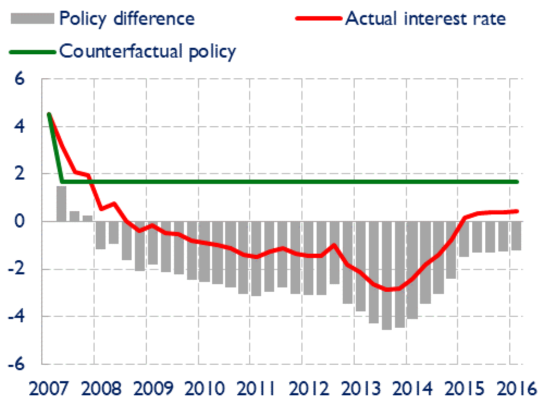
We first compare the combined impact of fiscal and monetary policies - i.e. we conduct a counterfactual policy scenario in both the (shadow) interest rate and government spending variables are constrained to their sample averages over the estimation period. We then look at the contributions of fiscal and monetary policies separately. To examine the contributions of monetary policy, we restrict only the path of the interest rate in the counterfactual policy scenario. To examine the contribution of fiscal policy, we restrict only the path of government spending.

The approach is illustrated for the United States in Figure 3.3. The left-hand side chart shows the actual path of the (shadow) interest rate and the counterfactual policy path (set to the sample average for the interest rate in the United States). The right-hand side chart then shows the GDP conditional forecast based of the actual policy rate (blue line) and the GDP path conditional on counterfactual policy (green line). Both scenarios imply a deep decline in 2008 and 2009 which reflects the effects of the global factors captured by the exogenous variables in the VAR. However, gradually differences in the path of (year-on-year) GDP growth emerge. Those differences (measured in the percentage point differences of GDP growth) are shown by the gray bars and aim to capture the policy impact of monetary policy in that period.

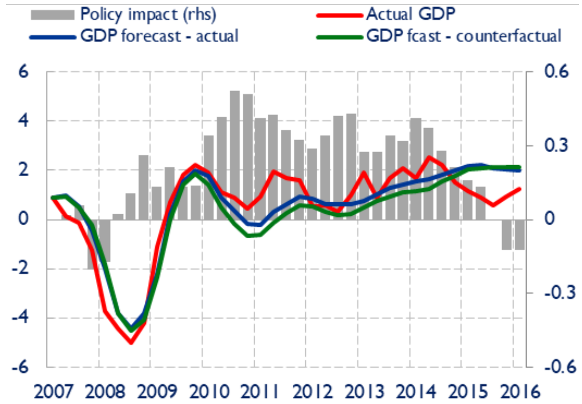
Note that we deliberately compare two conditional forecast scenarios – i.e. we compare the counterfactual policy scenario with another conditional forecast for GDP based on the

Figure 3.3: United States: Counterfactual scenario for monetary policy

(a) United States: Actual and counterfactual policy realisation for monetary policy (lines – percent; bars – percentage point differences)



(b) United States: Actual and counterfactual policy realisation for GDP growth (year-on-year percentage changes, lhs; percentage point differences, rhs)



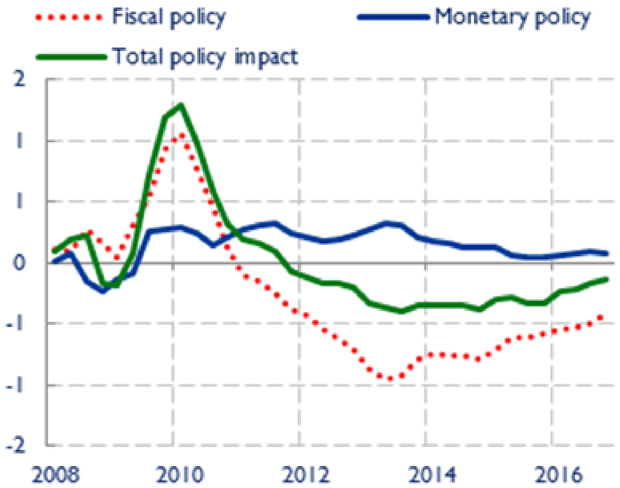
actual realisations of policy variables. Another option would have been to compare the counterfactual policy scenario with the actual realizations of GDP (i.e. the green line with the red line in Figure 3.3). But this strategy would have mixed the effects of policy with other factors that generated fluctuations in real activity over this period. Our method aims to isolate the policy contributions.

Note also that we employ a structural approach to understanding the contributions of policy. Lenza et al. (2010) and Kapetanios et al. (2012) use a similar approach to analyze the effects of quantitative easing in the euro area and UK respectively. However, they use a reduced form approach in which the path of the restricted variable is obtained through the contribution of all shocks. By contrast, we employ a strategy in which restrictions on specific structural shocks generate the fixed path of the conditioned variable. For example, in order to obtain the GDP forecast with the federal fund rate fixed at a predetermined value, we restrict (only) the monetary policy structural shock in such a way that it generates the desired fixed path for the monetary instrument (see Doan et al. 1983 and Waggoner and Zha 1999, Dieppe et al. 2017); no restrictions are placed on the other shocks which are drawn from their own distribution.[12] The main advantage of the structural approach in conducting the counterfactual analysis is that it captures the heterogeneity (across countries) of the policy contribution on GDP by taking into account the variability in the response of GDP to policy shocks as well as in the design of the specific policy measure. A detailed example of the counterfactual scenario is presented in the appendix.

The estimated overall support from government spending and monetary policy is shown in Figure 3.4 for the aggregate GDP of the countries in the sample, and at country level

[12]For example, in case of a recursive identification, an unrestricted shock is drawn from a N(0,1) distribution. See Dieppe et al. 2017 for details.

Figure 3.4: Policy contributions to aggregate GDP for eight countries (Percentage point difference in year-on-year GDP growth between actual policy and counterfactual policy scenarios)



Notes: the lines show the differences year-on-year GDP growth between actual policy and counterfactual policy scenarios (see section 3.2 for explanation). Green line shows the impact of fiscal and monetary policies combined; red dotted line shows impact of fiscal policy only; blue shows the impact of monetary policy. GDP growth is a PPP-weighted average of the 8 countries in the sample

in Figure 3.5.[13] The results suggest that global activity benefited from substantial policy support in the aftermath of the global financial crisis, as policymakers loosened both fiscal and monetary policy to combat the sharp downturn in economic activity. Moreover, the policy support faded quickly, and by 2011, policy acted as a drag on global activity. The shift was mostly driven by fiscal policies: while monetary policy remained accommodative, particularly in advanced economies, efforts towards consolidation provided a significant headwind to the global expansion. More recently, macroeconomic policies have become more supportive for global activity. The drag from fiscal policies consolidation has gradually lessened, particularly in advanced economies. With monetary policies remaining highly accommodative in advanced economies and some monetary easing in large EMEs, the overall contribution of policy to growth has shifted and become less negative.

The extent of policy support has varied strongly across countries and instruments, in particular after the initial support to the global financial crisis.

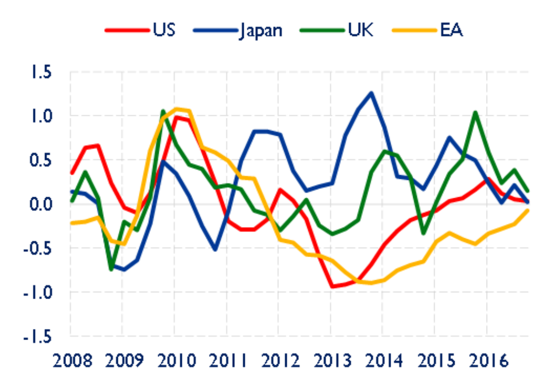
Specifically, in advanced economies (Figure 3.6), highly accommodative monetary policy has been counteracted by strong fiscal consolidation. After the initial support provided following the Great Recession, the support from fiscal policy in advanced economies faded quite rapidly, acting as a significant drag on economic activity.

In the United States, federal spending as part of the American Recovery and Investment Act started to wane, while state and local government spending continued to diminish from

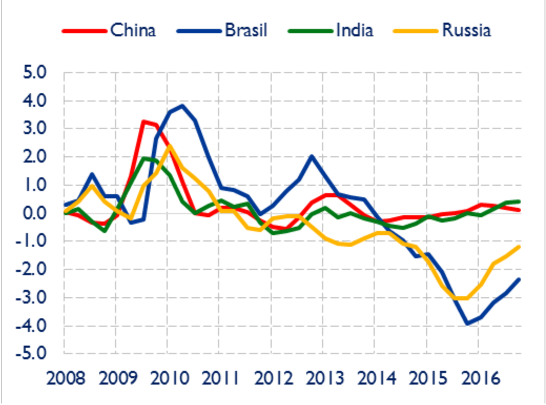
[13]For ease of exposition we limit our attention to the differences in the medians across the two scenarios. Figures S30 and S31 in the appendix report the full posteriors for both scenarios for the case of overall policy contribution.

Figure 3.5: Policy contributions to GDP growth for advanced and emerging economies (Percentage point difference in year-on-year GDP growth between actual policy and counterfactual policy scenarios)

(a) Advanced economies



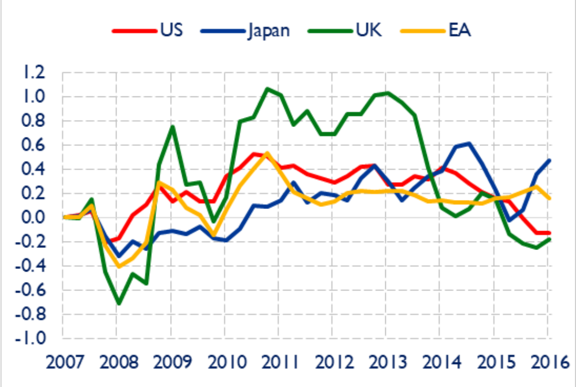
(b) Emerging economies



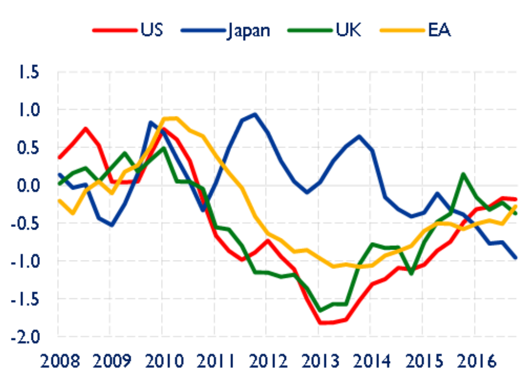
Notes: the lines show the differences year-on-year GDP growth between actual policy and counterfactual policy scenarios (see section 3.2 for explanation).

Figure 3.6: Policy contributions to GDP growth for advanced economies from monetary and fiscal policies (Percentage point difference in year-on-year GDP growth between actual policy and counterfactual policy scenarios)

(a) Monetary policy

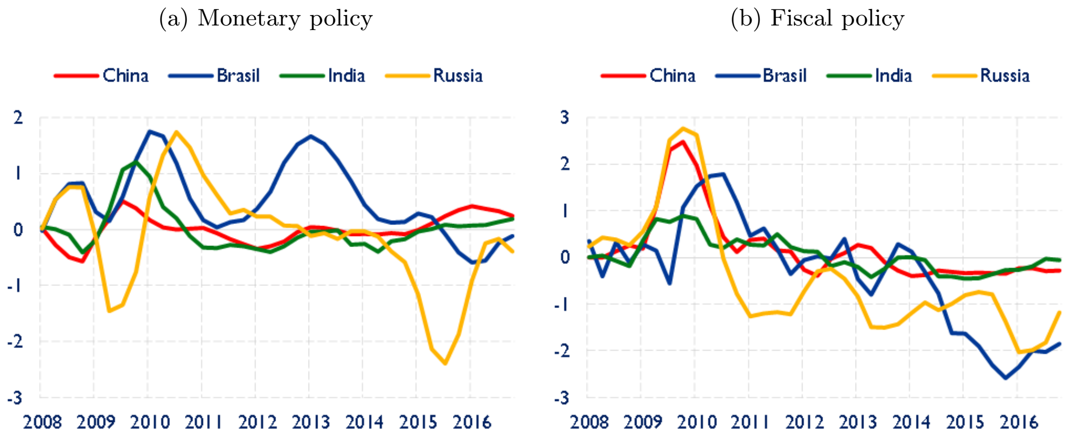


(b) Fiscal policy



Notes: the left-hand side chart shows the differences in year-on-year GDP growth between actual policy and counterfactual policy scenarios in which only the interest rate is restricted in the counterfactual policy scenario. the right-hand side chart shows the differences in year-on-year GDP growth between actual policy and counterfactual policy scenarios in which only the path of government spending is restricted in the counterfactual policy scenario. See section 3.2 for explanation.

Figure 3.7: Policy contributions to GDP growth for emerging market economies from monetary and fiscal policies (Percentage point difference in year-on-year GDP growth between actual policy and counterfactual policy scenarios)



Notes: the left-hand side chart shows the differences in year-on-year GDP growth between actual policy and counterfactual policy scenarios in which only the interest rate is restricted in the counterfactual policy scenario. The right-hand side chart shows the differences in year-on-year GDP growth between actual policy and counterfactual policy scenarios in which only the path of government spending is restricted in the counterfactual policy scenario. See section 3.2 for explanation.

2011 onwards, reflecting the states' balanced budget rules. In 2012-13 some fiscal measures expired (including the Bush income tax cuts for high-income households, the payroll tax reduction for middle-income households; and the extended unemployment benefits). More recently, however, policy has provided a more supportive backdrop: the drag from fiscal consolidation has eased, while monetary policy remained accommodative. In Japan, fiscal consolidation was delayed by the earthquake in 2011 which necessitated emergency spending. Monetary policy by the Bank of Japan through its quantitative easing program has increasingly supported GDP growth over the sample period. In the United Kingdom, the contribution from monetary policy has been a pillar of growth, but has become more neutral recently as the Bank of England has started to gradually remove its policy accommodation. Meanwhile fiscal policy has also become less of a drag over time after a long period of austerity. Finally, in the euro area fiscal policy was a major drag on growth. This can be explained by consolidation needs that arose due to the euro area sovereign debt crisis. However, the drag from fiscal consolidation has also diminished here. By contrast, monetary policy in the euro area has supported growth.

On the other side, in EMEs (Figure 3.7), monetary policy has been less accommodative since the global recession. In China, after the initial policy support during the global recession monetary policy tightened, with interest rates and reserve requirements remaining relatively high despite low inflation. Subsequently, as GDP growth slowed during 2014, lower interest rates and some fiscal support have provided for more supportive policy.

However, it is likely that our model does not fully capture the role of fiscal policy in China. IMF (2017c) estimates a significantly larger fiscal deficit than reported by official figures, suggesting substantially bigger fiscal support. Amongst other EMEs, the experience of commodity exporting EMEs (Brazil and Russia) has played an important role in shaping developments. Policy in these countries was broadly supportive for activity until 2014 when sharp terms of trade shocks forced a recalibration of policies. Monetary policy tightened in both countries to combat currency depreciation and high inflation and inflation expectations. Fiscal policies were also restrained – by high debt and weak credibility in the case of Brazil; and by the need to adjust to lower oil revenues in the case of Russia. With fiscal consolidation remaining a necessity in both countries, policies continue to act as a headwind to GDP growth, although some monetary easing - as currencies have stabilised and inflation has fallen - has provided some help.

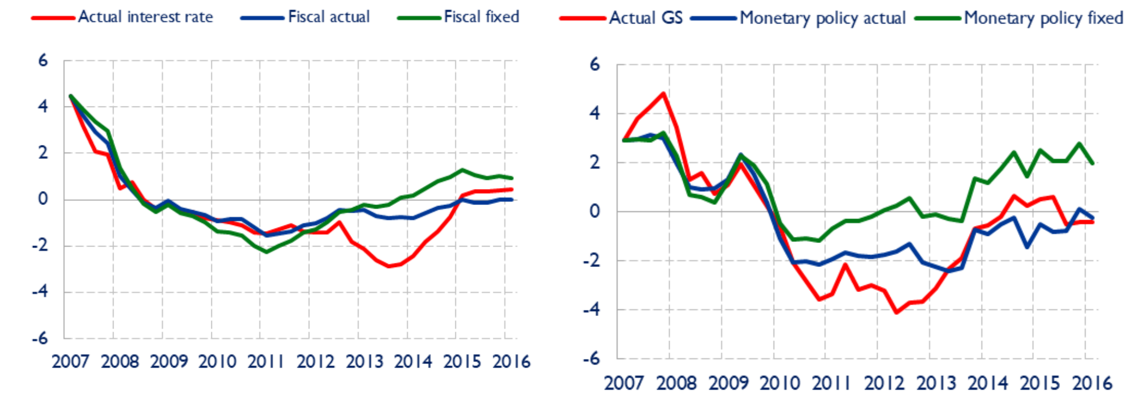
3.3.3 The interaction of monetary and fiscal policies

The empirical setting used in our analysis is well suited to analyzing the interaction and interdependencies of monetary and fiscal policies. In this section, we ask two questions: (i) how might monetary policy (MP) have behaved if fiscal policy (FP) had been conducted differently? and (ii) how strong would fiscal support have needed to be, had monetary policy been less accommodative? We illustrate the interactions using the US economy as an example, being one of the largest economies in our sample. We first assess the role of fiscal policies in shaping monetary policy since the global financial crisis. Following the methodology described in section 3.2 we conduct two conditional scenarios. In the first scenario we restrict shocks to government spending, tax, inflation and GDP to produce a conditional forecast for interest rates conditioned on the observed paths of GDP, inflation, tax and government spending. In the second scenario, we restrict the same shocks to obtain a path for interest rates conditioned on the actual values of GDP, inflation and tax but keeping government spending at its sample average (Figure 3.8 a). To compensate for the lack of the fiscal stimulus, the counterfactual paths for policy suggest a sharper reduction in (shadow) interest rates in the United States. Thereafter, however, fiscal consolidation has forced continued accommodation from monetary policy. Without the fiscal consolidation that occurred from 2011 onward, monetary policy would have begun to tighten already in the United States – indeed, our model suggests that interest rates would have been above the zero lower bound already in 2013. In other words, the results show how much of the monetary policy reaction was triggered by the additional effects on output and inflation generated by the government spending policy.

We next consider the reverse question and ask how fiscal policy might have behaved

Figure 3.8: Policy interaction scenarios for the United States

(a) Monetary policy (percent) (b) Fiscal policy (year-on-year percentage changes)



Notes: the left-hand side chart shows the actual and counterfactual paths for monetary policy from 2007. The red line shows the actual (shadow) interest rate path. The blue line shows the conditional forecast for the interest rate, conditioned on the observed profiles for GDP, inflation and government spending (from 2007 onwards). The green line shows the conditional forecast for the interest rate, conditioned on the observed profiles for GDP, inflation (from 2007) and with government spending fixed at the sample average. The right-hand side chart shows the actual and counterfactual paths for government spending from 2007. The red line shows the actual path of government spending (in year-on-year percentage changes). The blue line shows the conditional forecast for the government spending, conditioned on the observed profiles for GDP, inflation and the interest rate (from 2007 onwards). The green line shows the conditional forecast for government spending, conditioned on the observed profiles for GDP, inflation (from 2007) and with the interest rate fixed at the sample average.

had monetary policy been different. As before, we conduct two scenarios. In the first scenario we restrict shocks to GDP, inflation, tax and interest rates to produce a conditional forecast for government spending conditioned on the observed paths of GDP, inflation, tax and interest rates (blue lines in Figure 3.8 b). In the second scenario, we restrict the same shocks to obtain a path for government spending conditioned on the actual values of GDP, tax and inflation but keeping interest rates at the sample averages (red lines in Figure 3.8 b). The counterfactual scenarios highlight the role of accommodative monetary policies in allowing fiscal consolidation in the US after the global recession. In the scenarios without considerable monetary accommodation (i.e. the red lines), the model suggests that government spending would have needed to be stronger to support activity.

3.4 Robustness analysis

We perform additional robustness checks aiming to address some of the concerns raised by our analysis. More details on the sensitivity tests discussed in this section can be found in the appendix to the paper (Figures S25 - S29). Jarocinski (2010) and Gelman (2006) show that weekly informative prior for the parameter λ governing the model heterogeneity can have undesired effects on results, especially for panel with more than 5 units. In order to reinforce our results, we re-estimate the model using the uniform prior (with s= -1 and v=0) instead. Impulse response functions reported in Figure S25 Appendix are almost unaffected by this change.[14]

In choosing the lag structure for EMEs, we prefer a model with 6 lags. In addition we control for the monetary aggregate including M2 before monetary policy instrument. This model performs better in alleviating the price puzzle. However, for the AEs we adopt a 5 lag structure without M2 and there might be concerns on the validity of the statements regarding the comparison of policy effects across groups. Moreover, there is not a clear agreement in the literature on whether M2 should be placed before or after the policy rate. As such we check the effect of policy shocks on GDP in EMEs in two additional scenarios, specifically with 5 lags instead of 6 and with M2 ordered last. IRFs of GDP are mildly affected while price puzzle is a bit more pronounced in both cases. Additionally, since EMEs have to deal also with the excessive money growth rooted in the government‘s need to finance itself by seignorage (see Frankel, 2010), we perform a counterfactual check for EMEs in which monetary policy targets both the interest rate and the monetary aggregate. Results (see Figure S27) show an increase in the magnitude of the effects of monetary policy compared to the scenario of only interest rate targeting. We also test the sensitivity of our results to employing a different shadow rate for AEs in order to account for the ZLB. Figure S29 shows impulse responses of GDP for advanced economies to a monetary policy shock using the shadow rate measure proposed by Krippner. Finally, we check the convergence of the Gibbs sampler reporting the inefficiency factors for the posterior estimates of the parameters. The convergence diagnostics (Figure S32) are satisfactory with inefficiency factors values below 5 for all parameters.

3.5 Summary

We used Panel VARs with hierarchical structure to asses and compare the effects of fiscal and monetary policy to GDP growth in advanced and emerging economies. Our results suggest that the effects of monetary policy on GDP are similar across the two groups while the fiscal multipliers are higher in AEs compared to EMEs. We also find that fiscal policy effects display some within group variation. This effect is not verified in the case of monetary policy.

We then conducted a counterfactual analysis and we provided evidence that global GDP growth benefited from substantial policy support during the global financial crisis but policy tightening thereafter, particularly fiscal consolidation, acted as a significant

[14]Since the counterfactual scenario is constructed from pieces of IRFs, we are comfortable to assume that stable IRFs imply stable conditional forecasts.

drag on the subsequent global recovery. In addition we show that the role of policy has differed across countries. Specifically, in advanced economies, highly accommodative monetary policy has been counteracted by strong fiscal consolidation. By contrast, in EMEs, monetary policy has been less accommodative since the global recession.

Finally, our counterfactual scenarios emphasize the important interdependence of fiscal and monetary policies in shaping each other. The scenarios provide admittedly stark contrasts but they underscore the interdependence of each branch of macroeconomic policy. In particular, in United States, we find that fiscal consolidation in the aftermath of the financial crisis has pushed continued accommodation from monetary policy.

Chapter 4

Uncertainty shocks in emerging economies

4.1 Introduction

Following the 2008 global financial crisis an extensive literature focused on the concept of uncertainty and its role in driving the business cycle. Although there is no consensus from a theoretical perspective regarding the direction of causality between uncertainty and business cycle, substantial evidence associates higher uncertainty with recessions and several explanations have been put forward. If some studies consider uncertainty as a cause of the business cycle, postulating that higher uncertainty induces precautionary saving of households or "wait and see" behavior of firms (Bloom, 2009; Basu and Bundick, 2017; Leduc and Liu, 2017; Bloom et al., 2018), some others propose uncertainty as a consequence of the lower economic growth assuming that recessions encourage risky behavior or reduce the information (Bachmann and Moscarini, 2011; Ilut and Saijo, 2016).

The lack of theoretical consensus regarding the direction of causality between uncertainty and business cycle poses important challenges to the empirical studies aimed at analyzing the role of uncertainty for business cycle. Many of the previous econometric analyses identify uncertainty shocks using structural VARs with recursive identification (see, among others, Bloom, 2009; Bachman et al., 2013; Carriere-Swallow and Cespedes 2013; Caggiano et al., 2014; Caggiano et al. 2017; Meinen and Roehe, 2017). However, this approach has been shown to be inadequate (see Ludvigson et al. 2017) for two reasons. First, it is not clear whether uncertainty should be placed before or after the real activity variables. Second, there is no conclusive theoretical reason for ruling out the contemporaneous co-movement between uncertainty and real activity, which is an implicit assumption in the recursive structure.

A recent strand of the literature addresses the "potential endogeneity" of uncertainty by means of novel identification procedures. Specifically, Mumtaz (2018), Piffer and Podstawski (2017) and Redl (2018) rely on external exogenous instruments to identify uncertainty shocks showing that such shocks can be a source of economic fluctuations. Caldara et al. (2016) find similar results adoptiong a penalty function approach within a VAR framework. Carriero et al. (2018) and Angelini et al. (2018) instead exploit the heteroskedasticity of macroeconomic variables to relax the timing restrictions embedded in the Cholesky identification; they show that macroeconomic uncertainty can be considered exogenous while the financial uncertainty is more an endogenous response to macroeconomic conditions. In contrast, Ludvigson et al. (2017) mix event constraints with correlation constraints in a set identified framework to achieve identification for uncertainty shocks. They claim that macro uncertainty is endogenous while financial markets are a source of output fluctuations. Cesa-Bianchi et al. (2014) propose a common factor approach in a multi-country setting, placing restrictions on cross-country correlations, and argue that country-specific volatility shocks play a negligible role in determining the business cycle. In the light of these contrasting results the endogeneity of uncertainty remains an open debate.

Another challenge faced by the empirical studies aiming at validating the adverse effects of uncertainty shocks, is the lack of an objective measure of uncertainty; in fact several proxies have been employed in the literature. For example, Bloom (2009) proposes the stock market volatility as a measure for uncertainty, Baker et al. (2016) and Scotti (2016) focus on news based indicators, Bachmann et al. (2013) rely on business survey data to obtain uncertainty measures, Villaverde et al. (2011), Mumtaz and Zanetti (2013), Mumtaz and Theodoridis (2015), Alessandri and Mumtaz (2018) and Carriero et al. (2017) construct proxies of uncertainty based on the time-varying volatility of errors. Jurado et al. (2015) (hereafter, JLN) measure uncertainty as the unforcastable component of large sets of macro and financial variables, while Rossi and Sekhposyan (2015) infer uncertainty by means of forecast errors.

Although extensive research has been carried out on uncertainty shocks, little is known about the effects of such shocks in emerging economies. This lack of evidence can be largely attributed to the limited availability and accuracy of data for these countries.[1] However, the very few attempts made in this direction (Fernandez-Villaverde et al. 2011; Carriere-Swallow and Cespedes, 2013; Bhattarai et al., 2018), show that uncertainty shocks have large and detrimental macroeconomic effects in emerging countries raising the need for a

[1]Not only the macroeconomic variables in EMEs are available for short samples and they often involve episodes of high instability, but the uncertainty indicators proposed in the literature are mainly available for US and few other developed economies.

deeper understanding of the topic.

This paper explores the impact of uncertainty shocks in EMEs while addressing the endogeneity concern regarding the relationship between uncertainty and the real activity. To this purpose, we develop a novel Bayesian framework that combines the panel VAR with hierarchical structure à la Jarocinski (2010), with the methodology proposed by Caldara and Herbst (2018) and Rogers et al. (2016) for the estimation of Bayesian proxy SVAR models[2]. The model we obtain can be interpreted as a panel proxy VAR with random coefficients and it offers three key advantages. First, exploiting the cross section dimension of the data effectively deals with the limitations associated with the short samples. Second, the proxy extension accommodates the use of an instrumental variable approach for the shock identification; as such we do not rule out the potential co-movement between uncertainty and real activity. Finally, the hierarchical structure of the model allows for cross section heterogeneity which we examine in a regression analysis, to show that part of the differences across countries in response to uncertainty shocks can be linked to country characteristics.

The empirical exercise focuses on a group of fifteen EMEs which excludes big emerging economies aiming to strengthen the exogeneity of the instrument. Following the methodology proposed by JLN we construct a global uncertainty indicator, as well as domestic uncertainty measures for each country in the sample. One advantage of using JLN approach is that this method captures the predictability of the economy, rather than the volatility, providing a proxy for uncertainty which is closer (than volatility) to the theoretical notion of economic uncertainty. Another advantage is that using a rich data environment as advocated by JLN method, reduces the possibility of biases caused by omitting relevant predictive information.

To identify the domestic uncertainty shock we propose a global to local approach for identification, in the spirit of Nakamura and Steinsson (2014) and Mumtaz (2018). To be more specific, we use innovations in global uncertainty as a proxy for domestic uncertainty shocks. Our identifying assumption is that global uncertainty fluctuations are uncorrelated with any domestic shock in the model other than the domestic uncertainty shock. In other words, innovations in the global uncertainty index are not contemporaneously affected by domestic shocks occurring in the *individual* country in the sample[3]; to reinforce the instrument exogeneity assumption we deliberately exclude from the sample

[2]We have recently become aware of Bahaj (2019) who proposes an alternative algorithm to estimate a proxy VAR with a cross section dimension. The two algorithms have been developed independently and are different.

[3]This is similar to ordering the global uncertainty index before the country specific variables in a recursive framework. Ordering global variables before domestic variables is a fairly standard assumption for applications related to small open economies.

big emerging economies and major oil exporters. One concern might arise regarding the exclusion restriction condition which requires that the only channel through which global uncertainty innovations affect domestic economies is via their impact on the country uncertainty index. However, in a VAR setting the exclusion restriction condition is implicitly validated by the fairly standard assumption that the VAR is well specified[4]. In order to support the assumption that the VAR is well specified, we define a model that includes six endogenous variables with their lags and three global exogenous variables to control for world developments. Finally, even if the informational sufficiency of the VAR is not fully believed, the regression coefficients of the GDP residuals on the instrument are close to zero and non statistically significant for all the countries in the sample which provides evidence in favor of the exclusion restriction[5].

Our identification approach is appealing for two main reasons. First, the proxy SVAR approach accounts for the potential measurement error in the instrument[6]; moreover the shocks we identify can be labeled as *domestic* uncertainty shocks. The second reason is related to the quality of our instrument. We rely on fairly standard assumptions to support the exogeneity of the instrument; furthermore, we show that our instrument is far more relevant than two other instruments obtained from alternative measures of global uncertainty used in the literature, namely the VIX index of equity volatility and the economic policy index of Baker et al. (2016).

The main findings of the paper can be summarized thus. We show that uncertainty shocks, defined as changes in the country specific uncertainty that are exogenous to domestic economic conditions, have significant macroeconomic and financial effects on the EMEs. Specifically, a one standard deviation uncertainty shock leads, on average, to a persistent and substantial decline in the level of real GDP of about 1%, sharply decreases the stock prices with a peak effect of more than 7%, and depreciates the real currency by 0.6%. The shock generates negative co-movement between GDP and CPI, with an estimated increase in the price level of around 0.3%; the central bank reaction is ambiguous which is not surprising, considering the challenges posed by the negative trade-off between inflation and output. The model detects a certain degree of heterogeneity across countries in the response to uncertainty shocks which we examine in more detail in a regression analysis.

[4] A well-specified VAR implies that the VAR residuals are a linear combination of only structural shocks; as such global uncertainty innovations should affect the reduced form residuals only through their impact on the local uncertainty structural shock. If this condition does not hold we face an omitted variables issue and the assumption that the VAR is well specified fails.

[5] See S7 in the Appendix

[6] Proxy SVAR models treat the instrument as a partial measure of the structural shock of interest accounting for potential measurement error in the proxy. A more straightforward alternative is to use the proxy as a variable in the model in a so-called hybrid VAR; this approach, however, does not account for the measurement error in the instrument. See Caldara and Herbst, 2018 for a detailed comparison between hybrid and proxy SVAR approaches.

From this exercise we learn that countries that are wealthier, more integrated in the global chains, and with more efficient labor and financial markets are less sensitive to uncertainty shocks; in contrast, countries with more efficient good markets and a higher trade share are more affected by uncertainty shocks. Finally, a counterfactual analysis shows that in the absence of uncertainty shocks, the recessionary effects experienced by EMEs during the global financial crisis and the European debt crisis would have been substantially lower.

This article makes three important contributions. To begin with, to the best of our knowledge, this is the first paper that investigates the effects of domestic macro uncertainty shocks in emerging economies, while accounting for the potential co-movement between uncertainty and the real activity. Second, from a methodological point of view we develop a novel Bayesian algorithm to estimate an extended version of a panel VAR with random coefficients, which accommodates for the use of proxies for the shock identification. Finally, from an economic perspective, we propose the use of a global to local approach for the identification of domestic uncertainty shocks. Compared to the country-to-state level used in Nakamura ad Steinsson (2014) and Mumtaz (2018), the global-to-country level approach adopted in this paper implies a potentially less restrictive instrument exogeneity assumption.

Our paper is related to the large literature that studies the relationship between business cycle and uncertainty (see Bloom, 2014 and Ludvigson et al., 2017 for an excellent review of the literature). In particular, this paper builds on Mumtaz (2018), who uses variation in country uncertainty to identify state-level uncertainty shocks in US, with two main departures: first, the methodology we employ is different since we use a proxy SVAR framework, instead of a single equation IV regression model; second, we are interested in the effects of uncertainty shocks in a group of EMEs, rather than in the US state level response to such shocks. World variables have also been used to instrument for local uncertainty by Bonfiglioli and Gancia (2015); however they examine the effect of uncertainty on structural reforms in a panel framework. We also differ from previous studies analyzing the effects of uncertainty in EMEs, such as Carriere-Swallow and Cespedes (2013) and Bhattarai et al. (2018), in that we account for the potential measurement error in the proxy for the uncertainty shock; moreover our shock can be labeled as domestic uncertainty shock rather that global or US uncertainty shock. We share the concerns regarding the appropriateness of the recursive framework for uncertainty shock identification with Cesa-Bianchi et al. (2014) as well; however we differ in the methodology and scope, since they develop a common factor model rather than a Panel VAR, and they aim at quantifying the relative importance of country-specific vs global volatility shocks. From a methodological point of view, we build on the method of external instruments for SVAR identification introduced by Stock and Watson (2012) and Mertens and Ravn (2013)[7], and on the literature exploiting the cross section dimension in VAR models (see Canova and Ciccarelli, 2013 for a survey).

The remainder of the paper is structured as follows. Section 2 describes the model specification and estimation. Section 3 presents the data and the uncertainty measures. In section 4 we discuss the results obtained from both the VAR model and the regression analysis. In section 5 we run additional robustness checks while section 6 concludes. We relegate to the Appendix the detailed description of the data and the algorithm and some supplementary results.

4.2 Empirical model

In this section we describe the empirical model and we highlight the key points of the prior distributions and MCMC algorithm; we confine the details to the technical appendix.

4.2.1 The Panel Proxy SVAR with hierarchical structure

We assume that each country can be modeled as an individual VAR and information from all countries in the sample is then used to perform estimation.

Consider a set of countries c= 1,....,C. For each country we define the following proxy SVAR:

$$Y_{tc} = X_{tc}\beta_c + Z_t\theta + u_{tc} \tag{4.1}$$

$$u_{tc} = R_c\varepsilon_{tc} \tag{4.2}$$

$$u_{itc} = \gamma_{ic}M_t + \eta_{itc} \tag{4.3}$$

u_{tc} ~ N(0,Σ) are the reduced form residuals for country c, X_{tc} is the matrix of endogenous variables for country c while Z_t is a vector of exogenous variables common to all countries which enter the VAR equation at time t. For simplicity define $\Phi_c = \{\beta_c, \theta\}$ and $G_c = \{X_{tc}, Z_t\}$.

The reduced form shocks can be related to the underlying structural shocks as per 4.2; for convenience we call ε_1 the structural shock of interest and ε_2 the remaining shocks. The goal is to identify the first column of matrix R for country c.

[7]A non-exhaustive list of studies using external instruments in SVAR includes Gertler and Karadi (2015), Carriero et al. (2015), Piffer and Podstawski (2017), Redl (2018), Caldara and Herbst (2018), Rogers et al. (2016), Mumtaz et al. (2018)

In a proxy SVAR framework the standard VAR model described by 4.1-4.2 is augmented by a measurement equation which links the reduced form residuals to the instrument for the targeted structural shock. Following Rogers et al. (2016) we define the measurement equation as in 4.3.

η_{itc} ~ N(0,ω^2) are the residuals of the measurement equation, u_{itc} is the i^{th} residual where i= 1,.....N, represents the number of endogenous variables per country, M is the instrument for the structural shock ε_1.[8]

From the instrument validity assumptions which require that :

$$E(\varepsilon_1 M) = \alpha \text{ (Relevance condition)}$$

$$E(\varepsilon_2 M) = 0 \text{ (Exogeneity condition)}$$

it can be shown that the instrument identifies R up to a scale and sign. In particular, the first column of R, assumig a unit shock, can be estimated as follows:

$$R_{1c} = E(u_{2tc}M)/E(u_{1c}M) \tag{4.4}$$

Alternative ways of specifying a proxy SVAR model from a Bayesian perspective have been proposed by Caldara and Herbst (2018), who work with the model expressed in structural form, and by Drautzburg (2016) who performs inference analogous to inference in a SUR model transformed to obtained independently normally distributed errors.

The main departure of the model described by 4.1-4.3 from the standard proxy SVAR approach is that we exploit the cross section dimension of the data and we assume a hierarchical prior for $\mathit{\Phi}_c$ and γ_{ic} coefficients as follows:

$$p\left(\Phi_c \mid \bar{\mathit{\Phi}}, O_c, \tau\right) = N\left(\bar{\mathit{\Phi}}, \tau O_c\right) \tag{4.5}$$

$$p\left(\gamma_{1c} \mid \bar{\gamma}, \Xi_c, \lambda\right) = N\left(\bar{\gamma}, \lambda \Xi_c\right) \tag{4.6}$$

where O_c and $\mathit{\Xi}_c$ are standard Minnesota priors and reflect the scale of the data, $\bar{\mathit{\Phi}}$ and $\bar{\gamma}$ are cross sectional average coefficients updated during the sampling procedure. The crucial parameters in this setting are τ and λ who control the degree of heterogeneity in the model. As τ and $\lambda \to \infty$ the coefficients collapse to the country specific VAR values while for τ and $\lambda = 0$ the model is equivalent to the pooled estimator. Ideally, τ and λ should reflect a good balance between individual and pooled estimates. In a standard Bayesian framework

[8]Since we do not adopt a recursive identification the order of the variables has no implication for our object of interest (Impulse response functions).

$\bar{\Phi}$, $\bar{\gamma}$, τ and λ are parameters to be calibrated while in the current context they are treated as random variables and have their own distribution.

In brief, equations 4.5 and 4.6 reveal that country coefficients are assumed to be drawn from a common distribution centered around the cross sectional mean but are allowed to deviate from this mean at a higher or lower degree dictated by the value of the endogenously determined parameters τ and λ . Therefore, the posterior of Φ_c and γ_{ic} are weighted averages of the country specific OLS estimates and the prior mean defined in 4.5 and 4.6.

The hierarchical structure of the model offers several advantages which are relevant to our study. First the average impulse response function can be computed using the mean model coefficients $\bar{\Phi}$ and $\bar{\gamma}$ to obtain the estimates. Moreover, $\bar{\Phi}$ and $\bar{\gamma}$ contain information from the whole panel which is likely to improve the estimation precision. In addition, the hierarchical prior shrinks the country specific coefficients towards the common mean leading to a more efficient use of the data and more precise estimates of the unit specific coefficients. Finally, since we model each country as an individual VAR our empirical framework easily accommodates for (time) unbalanced data.

4.2.2 Prior specification and posterior sampler

Priors

Following Jarocinski (2010) and Dieppe et al. (2017) we assume diffuse priors for $\bar{\Phi}$, $\bar{\gamma}$, Σ and ω^2 and Minnesota type priors for O_c while Ξ_c is an identity matrix. Regarding τ and λ a common prior choice is an inverse Gamma distribution with shape parameter $s_0/2$ and scale $v_0/2$. Gelman (2006) shows that results can be sensitive to the choice of the values for s_0 and v_0 and suggest the use of a uniform prior with s_0 = -1 and $v_0 = 0$ for models where the number of units is greater than 5 which is the strategy adopted in this paper.

Algorithm

We build on Caldara and Herbst (2018) and Rogers et al. (2016) to draw from the posterior using a Metropolis Hastings (MH) within Gibbs algorithm.

For ease of exposition we split the parameters Θ in two groups, the VAR parameters and the IV parameters :

$$\Theta_{VAR} = \left\{\Phi_c, \Sigma_c, \tau, \bar{\Phi}, \right\} \text{ and } \Theta_{IV} = \left\{\gamma_{1c}, \bar{\gamma}, \lambda, \omega_c^2, R\right\}.$$

We define the joint likelihood of the VAR data (G) and the instrument data (M):

$$P\left(G, M \mid \Theta\right) = P\left(G \mid \Theta_{VAR}\right) P\left(M \mid \Theta_{IV}, \Theta_{VAR}\right) \tag{4.7}$$

and combining the priors with 4.7 we re-write the posterior as in Rogers et al. (2016):

$$P(\Theta \mid D) = P(\Theta_{VAR} \mid G)\, P(\Theta_{IV} \mid \Theta_{VAR}, G) \tag{4.8}$$

where D contains both G and M.

The non closed form conditional posteriors are the $\varPhi$ and Σ while the rest of the parameters are standard with a known distribution to draw from.

The algorithm can be summarized thus:

1. Draw $P(\Phi_c^{new} \mid \varTheta)$ and $P(\Sigma_c^{new} \mid \varTheta, \Phi_c^{new})$ using an Independence MH step in which the proposal density for Φ takes the form of the known posterior for the case of a Panel VAR with hierarchical prior (see Jarocinski, 2010) and the proposal density for Σ takes the form of the known inverse-Wishart distribution when classical diffuse prior is assumed. Accept the proposal with probability:

$$\alpha = min\left(\frac{P(\Phi_c^{new}, \varSigma_c^{new}, \tau, \bar{\Phi}, \gamma_{1c}, \bar{\gamma}, \lambda, \omega_c)}{P(\Phi_c^{old}, \varSigma_c^{old}, \tau, \bar{\Phi}, \gamma_{1c}, \bar{\gamma}, \lambda, \omega_c)} \times q\frac{(\Phi_c^{old} \mid \Phi_c^{new})}{(\Phi_c^{new} \mid \Phi_c^{old})} \times q\frac{(\varSigma_c^{old} \mid \varSigma_c^{new})}{(\varSigma_c^{new} \mid \varSigma_c^{old})}, 1\right)$$

2. Draw γ_{ic}, ω_c^2 and R_{ic} from known posterior distributions using a Gibbs sampler.

Run Steps (1)-(2) for each country c=1....N

3. Draw $\bar{\varPhi}$, $\bar{\gamma}$, τ and λ from known posterior distributions using a Gibbs sampler using the information from all countries.

Please note that the execution of steps (1) and (2) is based on an internal loop which scrolls across countries. Once completed the internal loop, the parameters specific to the hierarchical structure are drawn in Step 3 using information from the whole sample of countries.

We use 35,000 replications and base our inference on the last 15,000 replications saving one every 5 draws.

A Monte-Carlo experiment which indicates that the proposed algorithm performs well and some evidence in favor of convergence are presented in the appendix.

4.3 Data

4.3.1 VAR analysis data

In the empirical exercise we limit our attention to fifteen relatively small EMEs, namely Argentina (ARG), Chile (CH), Colombia (COL), Croatia (CR), Czech Republic (CZE), Hungary (HUN), Peru (PE), Philippines (PHI), Poland (POL), Romania (ROM), Singapore (SGP), Slovenia (SLO), South Africa (SAF), Thailand (THA), Turkey (TUR). We deliberately exclude from the sample big emerging economies such as China, India, Brazil and the oil exporter countries; we do so in order to insure the exogeneity of the instrument which requires that economies are small enough to avoid that domestic economic fluctuations affect the global uncertainty indicator. For each country we construct a VAR described by equations 4.1-4.3. The matrix of endogenous variables for country c includes the measure of domestic uncertainty, real GDP, CPI, interest rate (R), real exchange rate (REER) and a composite stock price index. To account for the world developments which can potentially affect the business cycle of EMEs, we follow previous studies and we add Z_t, a vector of exogenous variables common to all countries. Z_t contains a commodity price index, the OECD industrial production index as a proxy for world demand, the US Federal Fund Rate which captures the risk appetite, a constant and a linear trend. The variables are at quarterly frequency and run from 1997q2 to 2016q4 for nine countries while the sample span varies for the remaining six EMEs due to constraints arising from data availability and quality. We highlight that variables enter the model in log levels (apart from the interest rate which is in levels) and the data is not per-processed before estimation except for the seasonal adjustment; the uncertainty measures are standardized.

4.3.2 Measuring Uncertainty

We construct measures of uncertainty based on JLN method which captures the deterioration in the agents ability to predict economic outcomes.

In brief, the statistical measure of uncertainty is obtained aggregating over a large number of estimated uncertainties. Following Ludvigson et al. (2017) we define $y_{jt}^C \in Y_t^C = (y_{1t}^C, ... y_{NCt}^C)$ be a variable in category C. Then its h-period ahead uncertainty, $U_{jt}^C(h)$ is the volatility of the purely unforcastable component of the future value of the series, conditional on all information available. Specifically:

$$U_{jt}^C(h) = \sqrt{E\left[\left(y_{jt+h}^C - E\left[y_{jt+h}^C \mid I_t\right]\right)^2 \mid I\right]} \tag{4.9}$$

where I_t represents the information available. The time varying forecast error is computed allowing the prediction error to have time varying volatility; to clean for the predicable component using information from a large dataset, the forecast $E\left[y^{C}_{jt+h} \mid I_t\right]$ is taken from a factor augmented forecasting model. Using a stochastic volatility model, uncertainty is calculated as the conditional expectation of the time varying squared forecast error. Finally the uncertainty in category C is obtained as the average over the individual uncertainties of each series in the category.

In order to construct the global uncertainty measure we employ the dataset from Mumtaz and Musso (2018) which contains quarterly financial and macroeconomic variables from first quarter of 1960 to the fourth quarter of 2016 for 22 OECD countries. For each country a number of 20 variables is considered with series ranging from real activity variables, consumer prices, labor market variables, asset prices, interest rates, credit market variables, money, trade variables and exchange rates. In addition, the data-set includes 20 more international variables referring to international prices of commodities and some emerging markets indicators. In total there are 460 time series; the global uncertainty indicator is obtained as the average across uncertainty measures for each of the 460 series constructed according to equation 4.9.

Regarding the data used to construct the domestic uncertainty measures the sample runs from 1996Q1 to 2016Q4; however the sample span and number of series included for each country varies according to data availability. We complete the data-set prepared for the VAR analysis with measures of trade (import, export), unemployment, international liquidity, international reserves and money variables. The domestic uncertainty for each country is calculated as the average across the 1 period ahead uncertainty measures for the country specific series.[9]

Where necessary variables are log differences and seasonal adjusted. A detailed list of the series used and data sources is available in the Appendix.

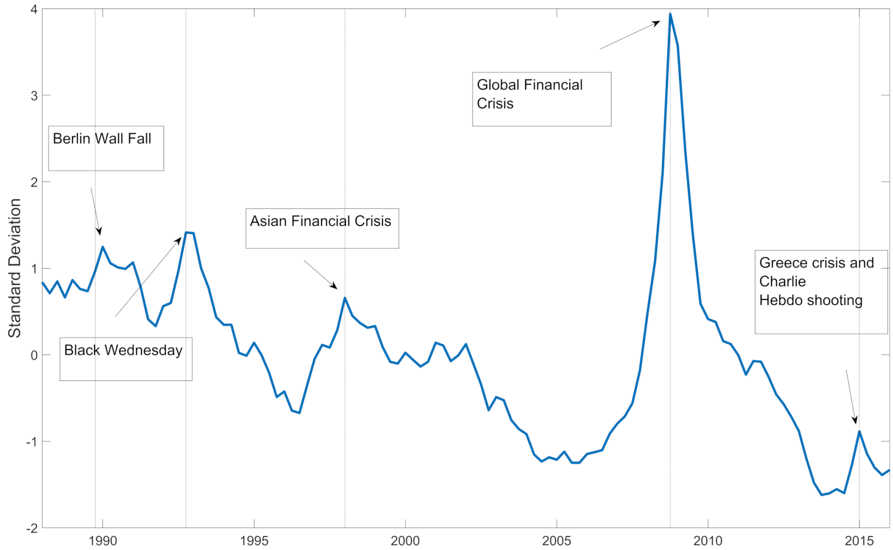
4.3.3 Uncertainty estimates

Figure 4.1 reports our estimate of global uncertainty. The measure recorded its highest peak during the recent financial crisis emphasizing the relevance of the recent recession for the OECD countries in the sample. The other peaks signaled by this measure coincide with the fall in the Berlin Wall, the black Wednesday currency crisis, the Asian financial crisis, the recent Charlie Hebdo terrorist attack and the Greek snap election following the plummeting of the stock prices at the end of 2014.

In Figure 4.2 we compare our proxy for global uncertainty with alternative measures

[9]The data-set used to extract the factors for the domestic uncertainties contains all EMEs data augmented by the OECD data from Mumtaz and Musso (2018).

Figure 4.1: Global Uncertainty Measure



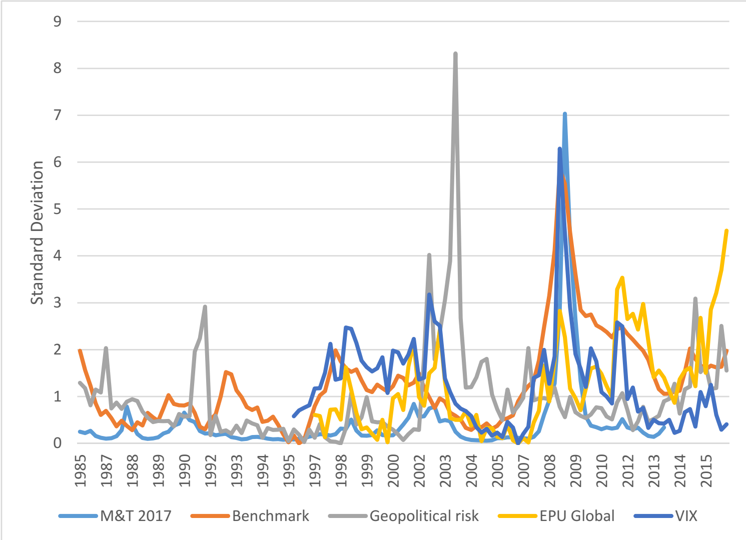
of global uncertainty such as the VIX, the measure proposed by Mumtaz and Theodoridis (2017) (hereafter M&T) which consists in the common standard deviation of the shocks to the world factors obtained from a dynamic factor model with time-varying volatility, the news based index of global economic policy uncertainty of Baker et al.(2016) (hereafter EPU) and the global geopolitical risk index of Caldara and Iacoviello (2018). Our measure displays some independent variation compared to the other indices and unsurprisingly it exhibits the highest correlation of 0.72 with M&T measure (which is also the most similar conceptually to our measure), followed by VIX and EPU with recorded correlations of 0.64 and 0.45 respectively. There is no correlation (-0.07) between our global uncertainty index and the geopolitical risk index suggesting that geopolitical events do not necessarily translate into higher global macroeconomic uncertainty or the other way around. [10]

Figure 4.3 shows the estimated country-specific uncertainty measures for the fifteen EMEs in the sample. It is interesting to note that the domestic uncertainty measure spikes around the recent global crisis for all countries. Moreover we detect peaks in uncertainty during events such as:

- recessions: Chile (1999), Czech Republic (1998-2000), Hungary (1998-2000 and 2003), Slovenia (1997 and 2000), South Africa (and 1997 and 2002), Poland (1998, 2000 and 2004)
- natural disasters: Philippines (typhoons 2011 and 2013), Thailand (tsunami 2004), Turkey (earthquake 2011)
- crisis: Peru (1999 credit crunch), Philippines (1997 financial crisis), Argentina (2014

[10] Notice that the geopolitical risk measure is the only one not spiking around the 2009 global financial crisis.

Figure 4.2: Alternative measures of Global Uncertainty



sovereign default)

- political instabilities and elections: Peru (2002 violent protests), Singapore (2015 Parliament dissolved), Thailand (2012 anti-government protests), Poland (2016 anti-government protests), Romania (2012 resignation of Prime Minister and referendum for president impeachment), Romania (2014 elections), Argentina (2015 elections), Chile (1999 elections)

4.4 Results

4.4.1 Instrument validity

Following Stock and Watson (2012) we use the residuals of an AR(2) regression of the proposed instrument, namely the global uncertainty index, as a proxy for the domestic uncertainty shock.[11] We claim that domestic uncertainty shocks can have a local origin (such as an earthquake) or a foreign origin (a global crisis). As such, innovations in global uncertainty index can be seen as a partial measure of the domestic uncertainty shock.

The instrument is considered valid if it is relevant and exogenous, i.e:

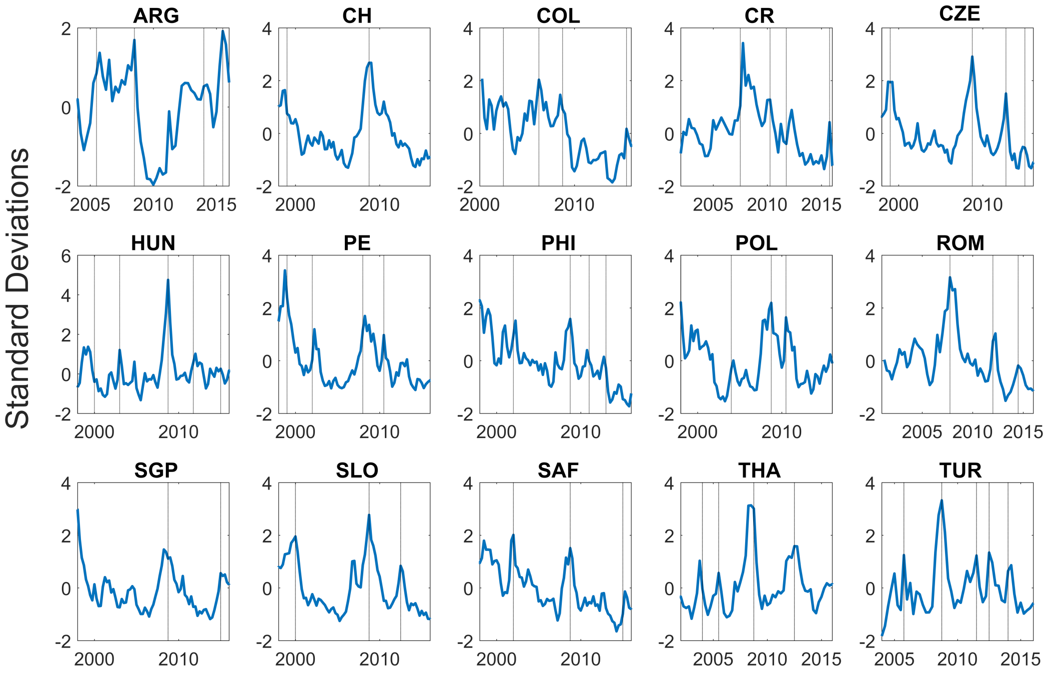
$$E(\varepsilon_1 M) = \alpha \text{ (Relevance condition)}$$

$$E(\varepsilon_2 M) = 0 \text{ (Exogeneity condition)}$$

The exogeneity of the instrument in a proxy SVAR framework requires that the proxy M, is uncorrelated with any structural shock in the model other than the domestic uncertainty shock. Since this condition is not testable, it relies on our identifying assumption

[11]We choose the length of the AR process using the AIC test.

Figure 4.3: Domestic Uncertainty



that business cycle fluctuations in small enough EMEs have no contemporaneous impact on the innovations in the global uncertainty index. In other words, fluctuations in the global uncertainty are exogenous to shocks occurring in small emerging countries. The exclusion restriction condition, which requires that global uncertainty innovations affect business cycle in EMEs only through their impact on domestic uncertainty, is not a concern in a well specified VAR setting in which the omitted variables issue is excluded by assumption. Moreover, the regression coefficient of the GDP residuals on the instrument (reported in the Appendix) are close to zero and not significant, reinforcing the validity of the assumption that global uncertainty is not an omitted variable in the country VAR model.

On the other side, the relevance of the instrument can be formally tested but it is a rather challenging task in proxy SVAR models since the instrumented structural shock is unobserved. Different methods have been proposed in the literature: some researchers approximate the relationship between the instrument and the structural shock of interest running F tests on the measurement equation (Gertler and Karadi, 2015; Piffer and Podstawski, 2017; Rogers et al., 2016), others report a squared correlation coefficient (Mertens and Ravn, 2013; Caldara and Herbst, 2018) while Drautzburg (2016) tests the validity of the instrument computing Bayes Factors under different scenarios.

Since performing a standard F test is not coherent with a Bayesian framework we address the relevance of the instrument in two ways. We report the posterior median estimates of γ_{1c} and 95% HPDI (see Table 4.1) and the ratio between the median estimates of γ_{1c} and their correspondent standard errors. Results suggest that the hypothesis of γ_{1c} being equal to zero is rejected for each country; moreover the value of the ratio between the measurement equation coefficients and their standard errors (Column 4 in Table 4.1) favors the hypothesis of a strong instrument[12]. In addition, in Figure 4.8 we show that our results are little affected when using different proxies, specifically the VIX and EPU, which have a considerably lower squared ratio compared to the benchmark case (average squared ratio between median estimate of γ_{1c} and its standard error is 28.84 for the benchmark model, 7.16 for VIX and 2.51 for EPU).

Finally, in the spirit of Drautzburg (2016), we use a goodness of fit statistic to check whether the instrument data brings useful information to the model. Specifically, we compute the Deviance Information Criteria (DIC)[13] for the benchmark model, and for a scenario in which the measurement equation contains a constant only. DIC test suggests that the benchmark model is preferred to the no instrument case with an average DIC value of 3227 for the benchmark scenario vs 3404 for the no instrument case. In the light of these results we are comfortable to claim that our instrument performs well in terms of relevance.

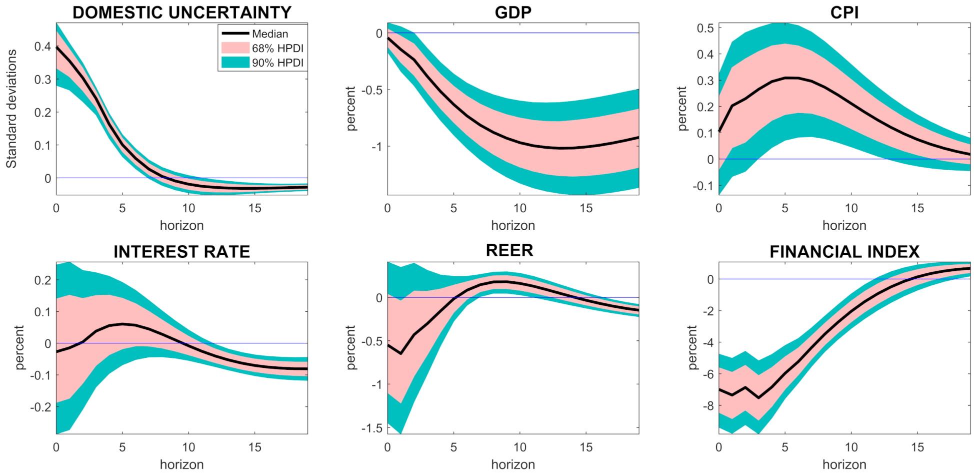
Table 4.1: Instrument relevance statistics. Benchmark case.

Country	Median γ_{1c}	95 HPDI	γ_{1c} /SE	DIC benchmark	DIC No Instrument
1	0.2328	(0.1496 ; 0.3445)	5.53	3615.36	3648.88
2	0.2404	(0.1591 ; 0.3329)	5.55	2600.70	2627.92
3	0.2449	(0.1646 ; 0.3424)	5.4	3468.10	3748.32
4	0.2258	(0.1334 ; 0.3122)	5.16	3864.41	3954.84
5	0.2300	(0.1408 ; 0.3138)	5.34	4026.92	4120.37
6	0.2321	(0.1439 ; 0.3196)	5.32	3242.27	3340.16
7	0.2373	(0.1391 ; 0.3115)	5.34	3561.53	3654.09
8	0.2365	(0.1551 ; 0.3225)	5.55	2177.46	2998.72
9	0.2352	(0.1542; 0.3238)	5.54	3742.28	3830.24
10	0.2343	(0.1470; 0.3241)	5.33	3501.69	3552.24
11	0.2363	(0.1364 ; 0.3126)	5.19	2581.06	3239.13
12	0.2263	(0.1377 ; 0.3158)	5.17	2757.92	2720.93
13	0.2275	(0.1527 ; 0.3261)	5.44	3299.37	3309.32
14	0.2315	(0.1455 ; 0.3202)	5.36	2913.23	3064.44
15	0.2345	(0.0673; 0.3262)	5.33	3064.63	3255.98
Average	0.2331		5.37	3227.79	3404.37

[12]In a classical perspective a value of the squared ratio between the measurement equation coefficient and its standard error, above 10 would suggest a strong instrument. Our estimates indicate a squared ratio value of 28.84 for the benchmark model.

[13]We rely on DIC test instead of Bayes factors since diffuse priors are assumed for several parameters which make the computation of Bayesian odds problematic (see Gelman et al., 2003).

Figure 4.4: Impulse response to a 1 standard deviation uncertainty shock in the average emerging economy. 68 and 90 HPDI bands reported



4.4.2 Results for the average emerging economy

We first report the results for an 'average' emerging economy computed using the posterior estimates of the average parameters $\bar{\Phi}$ and $\bar{\gamma}$. Figure 4.4 presents the posterior median of the response to a one standard deviation domestic uncertainty shock which increases the country uncertainty measure by 0.4 standard deviations. GDP does not respond to the shock on impact but it gradually falls reaching its peak of -1% after 12 quarters and the estimated effect displays high persistence. A sharp decline is observed in the stock price index of around -7% on impact and the detrimental effects the shock has on the financial variables are completely absorbed only after 15 quarters. Moreover the shock generates negative co-movement between CPI and GDP supporting the idea of a 'supply type' uncertainty shock in line with the conclusions reached in Villaverde et al. (2011a), Mumtaz and Theodoridis (2015) and Batharai et al. (2018). If we now turn to the REER and the policy rate, we observe that following an uncertainty shock the currency depreciates while the response of the monetary policy is ambiguous. This last result highlights the fact that these shocks pose serious challenges to the central bankers due to the negative trade-off between inflation and output.

Table 4.2 illustrates the contribution of the uncertainty shock to the forecast error variance of the endogenous variables. At short horizons the shock contribution is small for the macro variables while it explains a high share of around 25% of the financial index variability at all horizons. However, the shock becomes more important on medium-long horizons with a contribution to GDP of 12 and 15% after 3 and respectively 5 years while the contribution to CPI, REER and the policy rate remains small.

Overall our results regarding the impact of uncertainty shocks on GDP and CPI in emerging economies fall in the range of previous findings analyzing the effects of such shocks in US (Mumtaz and Theodoridis, 2015; Carriero et al. 2015; Caldara et al. 2016; Carriero et al. 2018); in change we estimate more severe disruptions of financial markets in EMEs compared to values reported for developed economies. Interestingly, our results are also qualitatively similar to Batharai et al. (2018) who instead focus on spillover effects from US uncertainty shocks in emerging markets suggesting that whether the origin of the uncertainty shock is domestic or foreign does not have important implications for the transmission mechanism of the shock.[14]

In summary, these results show that uncertainty shocks have substantial consequences in emerging economies leading to disruptions in both real and financial sectors. Moreover we estimate a negative co-movement in GDP and CPI; this poses additional constraints to the monetary authorities which cannot easily mitigate this type of shock.

Table 4.2: Variance decomposition for the average country. Posterior median with 68 percent HPDI in parenthesis

Horizon	Uncertainty	GDP	CPI	R	REER	Financial index
4 Q	0.90	0.02	0.03	0.02	0 .03	0.24
	(0.87,0.92)	(0.01,0.05)	(0.01,0.08)	(0.01,0.06)	(0.01,0.1)	(0.17,0.31)
8 Q	0.81	0.08	0.03	0.02	0 .03	0.26
	(0.76,0.84)	(0.05,0.13)	(0.01,0.08)	(0.01,0.06)	(0.01,0.1)	(0.20,0.33)
12 Q	0.73	0.12	0.05	0.02	0 .03	0.26
	(0.68,0.78)	(0.07,0.18)	(0.02,0.11)	(0.01,0.06)	(0.01,0.1)	(0.20,0.33)
20 Q	0.68	0.15	0.05	0.03	0 .03	0.25
	(0.61,0.72)	(0.10,0.21)	(0.01,0.10)	(0.02,0.07)	(0.01,0.09)	(0.19,0.31)

4.4.3 Heterogeneity across countries

Our empirical framework is well suited to compute country specific results as well. In particular, the unit specific coefficients are drawn from a distribution centered around the cross section average coefficients $\bar{\Phi}$ and $\bar{\gamma}$ with a tightness dictated by the parameters τ and λ. Given that the empirical literature is mainly concerned with the recessionary effects of uncertainty shocks, in this section we limit our attention to the response of GDP to such shocks. Country results regarding the remaining variables are provided in the Appendix. Figures 4.5 and 4.6 plot the GDP impulse responses (scaled across countries to increase the domestic uncertainty by 1 unit) and respectively the GDP variance decomposition estimates for each country in the sample. Results show that the model detects a certain

[14] An analogous result is reported in Mumtaz and Theodoridis, 2015 who show that uncertainty shocks originating in US have similar effects in both US and UK

Figure 4.5: GDP impulse responses. Posterior median estimate for each country. The shock is scaled to increase the country uncertainty by 1 unit.

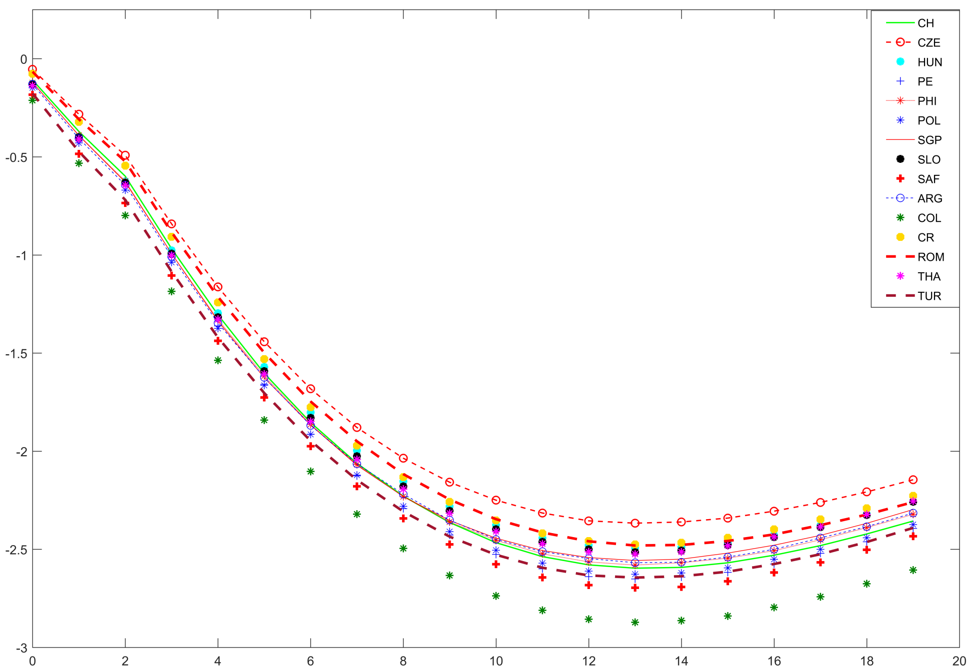
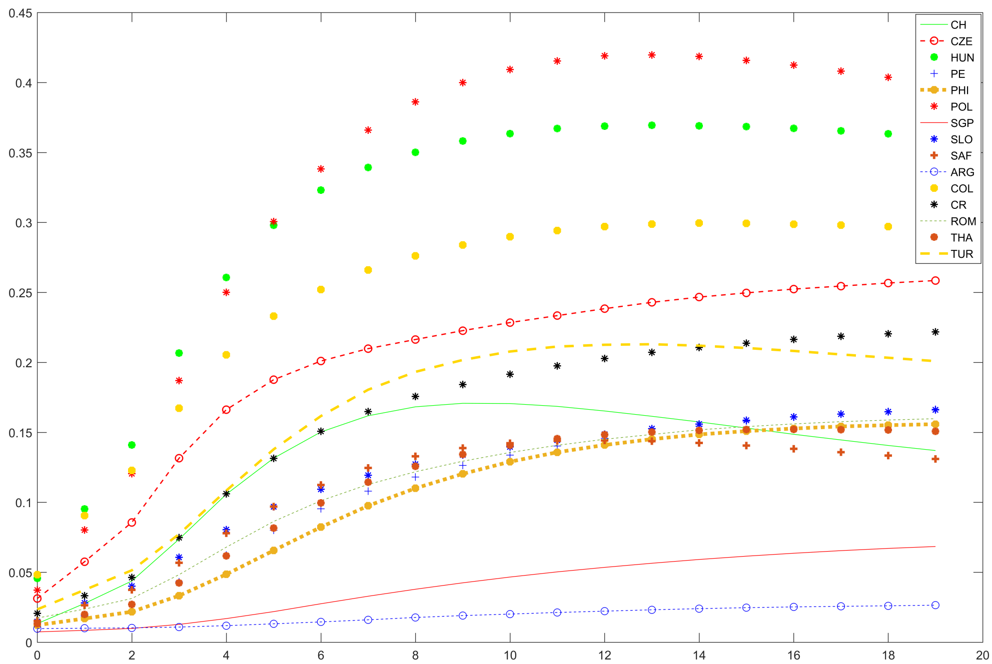


Figure 4.6: GDP variance decomposition. Posterior median estimate for each country.



degree of heterogeneity which translates into different scale of responses to shocks. Their shapes however are similar and close to those of the mean model responses, a finding in line with Jarocinski (2010). In terms of impulse responses, the most recessionary effects are experienced by Colombia, followed by South Africa, Poland and Turkey while the less affected economies appear to be Czech Republic, Romania and Croatia. If instead we turn our attention to the variance decomposition, our estimates suggest that uncertainty shocks explain a higher share of the GDP variability for countries such as Poland, Hungary and Colombia while in Argentina and Singapore uncertainty shocks explain a negligible share of GDP fluctuations.

We further explore the heterogeneity in the effects of uncertainty shocks on GDP in a regression analysis. Following Carriere-Swallow and Cespedes (2013) and Clayes and Vasicek (2017) we consider regressors such as: the degree of dollarization reported by Levy Yeyati (2006) to measure the importance of the currency denominated debt, domestic credit to private sector as a proxy for financial depth, GDP per capita, trade (% of GDP) as a proxy for country openness and the Herfindahl-Hirschman index of product concentration which is also related to the degree of product diversification. If the theory predicts that the degree of openness has ambiguous effects on the capacity of a country to absorb shocks, more diversified economies should be more resilient to adverse fluctuations. We also include manufacturing value added (% of GDP) as a proxy for integration in the global value chains and labor market and goods market efficiency indexes to account for economic flexibility. The sub-set of preferred regressors is chosen via the leaps-and-bounds algorithm of Furnival and Wilson (1974). The ranking of the relevant regressors is further confirmed by the spike and slab variable selection algorithm as per Koop (2016) (see Table S8 in the appendix).

IRFs are scaled across countries and represent the response of economy to a shock that increases the uncertainty measure by 1 unit; GDP cumulative impulse responses and variance decomposition, twelve quarters ahead, are regressed against the sub set of chosen regressors.

Table reports the results from the preferred specification for the two dependent variables, the GDP IRFs (first column) and variance decomposition (second column) corresponding to the uncertainty shock. In line with previous studies our estimates of GDP impulse responses show that countries that are wealthier, more integrated in the global value chains and with efficient labor markets suffer less severe GDP losses from uncertainty shocks while the efficiency in the goods market seems to enhance the recessionary effects of such shocks. One way of explaining this less intuitive result is that countries with better quality of institutions and business regulations attract and rely more on investment (domestic and foreign) which according to some studies, is one of the most affected GDP

Table 4.3: Country characteristics and uncertainty shocks. The dependent variables are GDP cumulative IRFs and Variance decomposition, 12 quarters ahead.

VARIABLES	(1) GDP IRF	(2) GDP vardec
GDPpc (log)	1.571	-0.203
	(0.540)	(0.0451)
Dollarization	2.341	-0.281
	(1.335)	(0.0619)
Manufacturing	0.137	-0.0296
	(0.0550)	(0.00386)
Trade		0.00260
		(0.000397)
Credit to private sector		-0.00268
		(0.000550)
Goods mkt efficiency	-1.271	0.211
	(0.527)	(0.0341)
Product concentration		-0.0260
		(0.0171)
Product diversification		-0.0134
		(0.00744)
Labor mkt efficciency	1.877	
	(0.568)	
Constant	-38.94	2.004
	(6.047)	(0.482)
Observations	14	14
R-squared	0.751	0.953

Robust standard errors in parentheses

component following an uncertainty shock.[15] A similar message is delivered also by the variance decomposition specification.[16] In addition, from the second regression we learn that countries with more developed financial sectors and with a higher degree of dollarisation are less sensitive to uncertainty shocks, while a greater trade share corresponds to a bigger vulnerability to such shocks.

However possible bias in the findings of the regression analysis might arise due to the small sample size; therefore these results should be interpreted with caution.

4.4.4 Counterfactual analysis

Up to know this paper has shown that uncertainty shocks have a substantial effect on macroeconomic and financial variables. However, little has been said about the importance of such shocks from an economic perspective. We conclude this section with a counterfactual exercise aiming to provide a model-based narrative on the historical role played by uncertainty shocks in shaping the GDP growth fluctuations. The question of interest is how different would have been the GDP growth in the absence of uncertainty shocks?[17]

The analysis involves three steps. First, we reconstruct the historical series of structural shocks. This step involves solving numerically for the entire matrix R, which links the reduced form residuals to the structural shocks; we impose a recursive structure for the remaining shocks[18]. We then replace the sequence of structural uncertainty shocks with zero and we recompute the reduced form residuals accordingly. Finally we simulate the evolution of GDP growth under this new sequence of residuals.[19]

Figure 4.7 illustrates the results. For each country we report the difference in the GDP growth under the counterfactual assumption of no uncertainty shocks and the actual data. Our estimates suggest that without uncertainty shocks the GDP growth would have been more than 2% higher during the global financial crisis for almost all countries in the sample. Moreover, it is interesting to notice that according to our model, all European countries in the sample experienced recessionary effects during the European debt crisis which can be attributed to uncertainty shocks. Our results also reveal that in the early 2000s when

[15]Carriere-Swallow and Cespedes, 2013 show that following an uncertainty shock in EMEs the drop in investment is around -4% while the decrease in consumption is around -1.2%. Bloom et al. 2018 report a negative reaction in investment and consumption of - 30 and respectively -2% following an uncertainty shock combined with a first moment productivity shock .

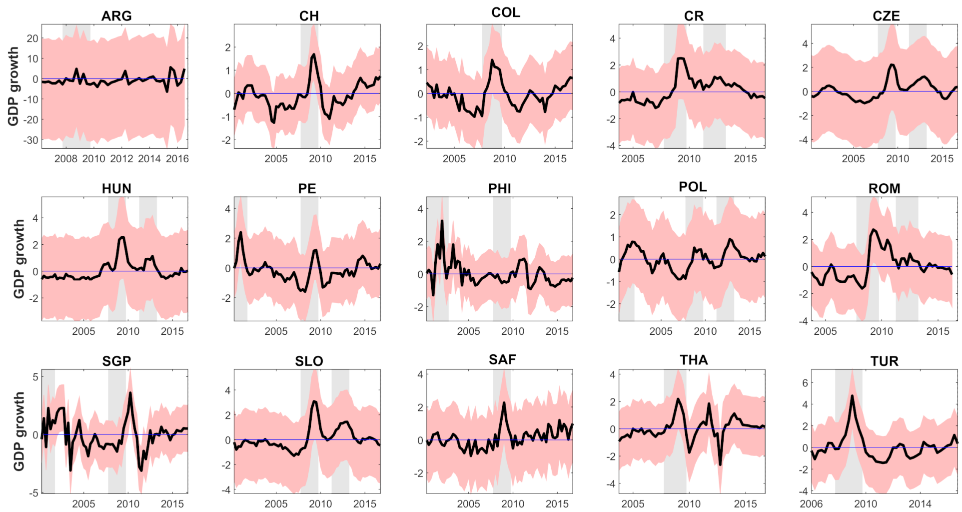
[16]The same regressors are significant in both specifications with opposite sign.

[17]For ease of exposition in this exercise we focus on GDP growth rather than levels.

[18]In order to identify the 6x6 R matrix we need to impose ten additional restrictions to the five restrictions obtained using the instrumental variable approach. We impose a recursive structure for the remaining shocks in a way that we do not restrict the contemporaneous response of uncertainty to the other shocks, as if uncertainty had been ordered last in the model.

[19]Since we do not change the values of the parameters, this exercise is not subject to the Lucas' critique as per Benati, 2010

Figure 4.7: Counterfactual scenario. The figure shows the difference between the GDP growth series generated under the counterfactual assumption of no uncertainty shocks and the actual data. The gray bands identify the global financial crisis, the Euro debt crisis for European countries and some selected recessionary episodes. 68 HPDI bands are reported.



internet bubble burst, uncertainty shocks had particularly detrimental effects in countries with pre-existing vulnerabilities, such as Singapore and Philippines (which were recovering from the Asian crisis) and Peru (which experienced a credit crunch in 1999). Finally, we signal also the 2000-2002 recession in Poland which can be partly explained by uncertainty shocks.

Summing up, the counterfactual analysis shows that uncertainty shocks were an important driver of the GDP fluctuations in EMEs; our results provide evidence on the relevance of the uncertainty shocks in emerging markets from an economic point of view, strengthening the usefulness of our findings.

4.5 Sensitivity analysis

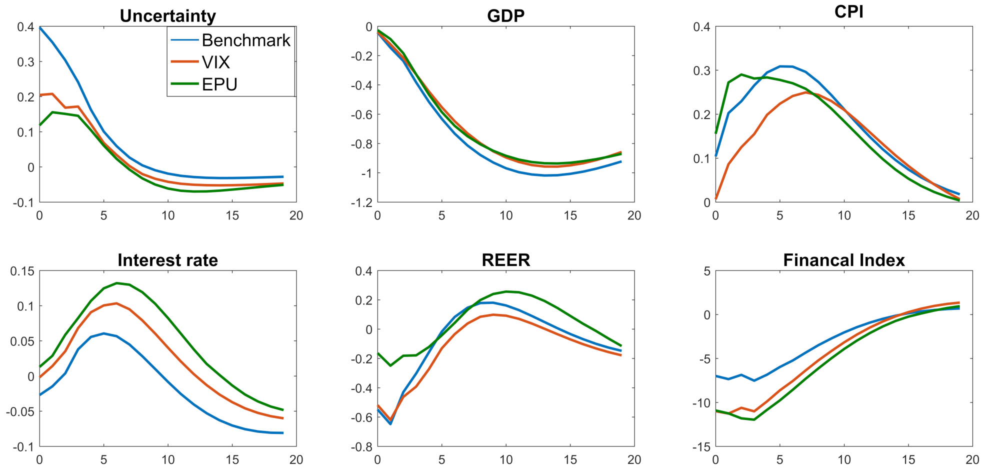
We perform an additional sensitivity analysis to check the robustness of the results. We provide a summary description in this section; detailed results are available in the appendix.

First we test the sensitivity of our findings to the proxy employed in the VAR exercise. To this end, we re-estimate the model using two alternative proxies, specifically the residuals from an AR(2) and an AR(1) regressions of VIX and respectively EPU.[20] Figure 4.8 shows the posterior median of the impulse responses across the three specifications of the instrument. We notice that results are fairly stable.

Additionally, we re-estimate the benchmark model with the following modifications:

[20]The length of the AR process is again chosen via AIC test and suggests an AR(2) model for VIX and an AR(1) model for EPU.

Figure 4.8: Posterior median impulse responses across different instrument specifications. Average country results.



no linear trend; linear and quadratic trend; the world demand proxied by Kilian's index of global real economic activity instead of the OECD industrial production index. The results are robust to these checks as well.

4.6 Summary

The aim of this paper is to examine the effects of uncertainty shocks in emerging economies. To this end we develop a novel Bayesian algorithm to estimate a model that combines a panel VAR with random coefficients with a proxy SVAR approach. This model deals in an efficient way with the lack of data availability for emerging markets while preserving the advantages of a proxy SVAR approach.

In the empirical exercise we limit our attention to fifteen small EMEs. We construct global and domestic uncertainty measures using the approach proposed by JLN. To identify the uncertainty shock we use innovations in global uncertainty as a proxy for the domestic uncertainty shock assuming that global uncertainty fluctuations are exogenous to business cycle developments occurring in a particular country in the sample.

We show that positive uncertainty shocks generate a persistent drop in real GDP and a severe decline in stock prices. The same shock causes a negative co-movement between real GDP and CPI while the monetary authority reaction is ambiguous.

We then turn to the country specific results and find evidence of cross country heterogeneity in responses to uncertainty shocks. We examine further this variability in a regression analysis. We notice the presence of statistically significant correlation between heterogeneity in the magnitude of GDP impulse responses to uncertainty shocks and selected cross country characteristics. In particular, countries that are wealthier, with higher share of manufacturing and with more efficient labor markets experience less recessionary effects following uncertainty shocks; countries with more efficient goods market and with a higher trade share are more affected by such shocks. Finally, a counterfactual exercise reveals that uncertainty shocks were an important driver of the GDP growth fluctuations in EMEs.

Chapter 5

Concluding remarks

The aim of this thesis was to explore different aspects of the domestic and international transmission of macroeconomic shocks from an empirical perspective. The methodology employed consisted in structural VAR models estimated using a Bayesian approach which allowed for more flexibility in dealing with non-linearities and models with a hierarchical structure. A more detailed description of the chapters is given below:

Chapter 1 focused on the role of IMF programs on the external vulnerability of a country. Even if one of the Fund's primary purposes consists in "advising member countries on economic and financial policies that promote stability, reduce vulnerability to crises, and encourage sustained growth and high living standards"[1] very little empirical literature analyzed the efficiency of the Fund in helping countries to reduce their vulnerability to external shocks. Trying to fill part of this gap, the first chapter addressed this explicit, although less often studied goal of the IMF programs. The methodology proposed was a bilateral BVAR model considered for 165 countries. From the variance decomposition of the estimated VAR models, a measure of external exposure was then built as the average effect of a set of external shocks on domestic variables. The BVAR results show that countries under Fund-supported loans have a smaller sensitivity to external shocks compared to countries without IMF program. The effect of participation in IMF programs on the external exposure of a country was then further investigated in a cross section analysis. Controlling for the potential endogeneity by instrumenting the IMF participation with the size of the IMF quota, the final set of results convey that IMF participation significantly decreases the external vulnerability of member countries.

Chapter 2 addressed the state dependency of a spillover index calculated for a group of seven advanced economies. Using a nonlinear setting, the analysis focused on the asymmetry of the connectedness index over the business cycle. The methodology employed

[1]www.imf.org

consisted in the estimation of a Threshold VAR model. The results suggest that during recession countries tend to be more connected and the estimated difference is large and statistically significant. In addition, negative shocks are found to have higher impact on the connectedness index compared to their positive counterparts. Moreover, financial and inflation shocks are assessed to be important determinants of global connectedness, and the connectedness indexes for these variables display a different behaviour compared to the real activity ones. Specifically, both inflation and financial connectedness are large and less state-dependent than the IP index. Financial shocks are important drivers of the cross-country connectedness in real variables, especially during recessions, while the opposite effect is not verified. These results reinforce the idea that movements in financial markets could lead economic activity. Cross-country inflation connectedness is higher in the long run, which is consistent with the shared long term objectives of monetary policy makers. Among the analyzed countries, the US and Japan are the main "shock givers" while European countries tend to be more shock "takers". A counterfactual exercise illustrated how relevant connectedness was from an economic point of view and reinforced the necessity to account for its state-dependent behaviour.

Chapter 3 aimed to asses and compare the effects of fiscal and monetary policy on GDP growth in advanced and emerging economies Using panel VAR models with a hierarchical structure, the results indicate that the effects of monetary policy on GDP are similar across the two groups while the fiscal multipliers are higher in AEs compared to EMEs. By means of a counterfactual analysis, the article then provided evidence that global GDP growth benefited from substantial policy support during the global financial crisis but policy tightening thereafter, particularly fiscal consolidation, acted as a significant drag on the subsequent global recovery. In addition it is shown that the role of policy has differed across countries. Specifically, in advanced economies, highly accommodative monetary policy has been counteracted by strong fiscal consolidation. By contrast, in EMEs, monetary policy has been less accommodative since the global recession. Finally, the counterfactual scenarios emphasized the important interdependence of fiscal and monetary policies in shaping each other. In particular, in United States, results show that in the aftermath of the financial crisis fiscal consolidation has pushed continued accommodation from monetary policy.

Chapter 4 examined the effects of uncertainty shocks in emerging economies. The empirical model applied in this analysis combines a panel VAR with random coefficients with a proxy SVAR approach. Such model deals in an efficient way with the lack of data availability for emerging markets while preserving the advantages of a proxy SVAR approach. A novel Bayesian algorithm has been developed to estimate the proposed model. The empirical exercise focused on fifteen small EMEs. Global and domestic uncertainty measures were constructed using the approach proposed by JLN. To identify the uncertainty shock, innovations in global uncertainty were used as a proxy for the domestic uncertainty shock assuming that global uncertainty fluctuations are exogenous to business cycle developments occurring in a particular country in the sample. The estimates point out that positive uncertainty shocks generate a persistent drop in real GDP and a severe decline in stock prices. The same shock causes a negative co-movement between real GDP and CPI while the monetary authority reaction is ambiguous. Turning to the country specific results, the analysis brought evidence in favor of cross country heterogeneity in responses to uncertainty shocks. This variability was further examined in a regression analysis and the findings indicate that countries that are wealthier, with higher share of manufacturing and with more efficient labor markets experience less recessionary effects following uncertainty shocks; countries with more efficient goods market and with a higher trade share are more affected by such shocks. Finally, a counterfactual exercise revealed that uncertainty shocks were an important driver of the GDP growth fluctuations in EMEs.

Appendix Chapter 1

S1 Robustness checks

The validity of our results is further tested in two additional checks. In the first subsection, we run a sensitivity analysis to the identification strategy. In the second subsection, we use World variables (instead of US variables) to capture the external shocks.

S1.1 Sensitivity analysis

In order to preclude that our results derive from the identification strategy employed, we consider a specification of the BVAR model in which both the external and domestic shocks are identified through the Cholesky decomposition. In the baseline model the variance decomposition of the most affected countries was between 9-18%, while when using the Cholesky factor, the correspondent interval becomes 11-22%.

The results reported in Figure S1 are similar to the ones obtained using sign restriction reinforcing the validity of our findings.

S1.2 World shocks robustness analysis

In this subsection, we test the appropriateness of using US variables to identify the external shocks. We replace the US variables with World variables. Hence, instead of US GDP, US CPI and US Interest rate we use World GDP, World CPI, and World Interest rate. All world variables are obtained from the IFS database, at quarterly frequency since 1970. We adjusted the database accordingly and dropped 10 additional countries. The results of the BVAR analysis (Figure S2) support the hypothesis that countries under IMF program are on average less sensitive to World shocks compared to countries not under IMF program. At the country level, as expected (given the geographical proximity and trade links with the US), the Latin American countries are slightly less sensitive to world shocks compared to US shocks. The same effect is verified for the Middle East oil exporters if we consider that US is one of the major oil importers. On the other side, China is highly vulnerable to world shocks but not to US shocks. The regression analysis reinforce the negative and significant impact of participation into IMF programs on the exposure to adverse external shocks.

Summing up, our results are robust to both the identification strategy and the model heterogeneity while US variables are shown to be an appropriate choice for the external block.

Country-model list

Country	Model[1]	Country	Model
Afghanistan	3x 2 (CPI and X)	Egypt	3x4 (CPI Trade Res X)
Albania	Complete. Only IMF period.	El Salvador	3x4 (GDP CPI Trade RES). No IMF period.
Algeria	Complete.	Estonia	Complete.
Angola	Complete.	Ethiopia	3x3 (CPI Trade X)
Antigua and Barbuda	3x3 (CPI R RESERVE)	Fiji	3x3 (IP CPI RES)
Argentina	Complete.	Finland	Complete.
Armenia	Complete. Only IMF period.	France	Complete. No IMF period.
Australia	Complete.	Gabon	3x3 (CPI R RES)
Austria	Complete. No IMF period.	Georgia	Complete. Only IMF period
Azerbaijan	3 x2 (UNEMPLOYMENT CPI). Only IMF period	Germany	Complete. No IMF period.
Bahamas	3x3 domestic. No IMF period.	Ghana	3x4 (CPI Trade R Res)
Bahrain	3x4 domestic (CPI R RES X). No IMF period.	Greece	3x4 (GDP CPI Trade RES)
Bangladesh	Complete. Only IMF period.	Grenada	3x3 (CPI Trade RES)
Barbados	3x4 (IP CPI TRADE RESERVE)	Guatemala	Complete. No IMF period.
Belarus	3x3(GDP CPI TRADE)	Guinea	3x2 (CPI Trade). Only IMF period
Belgium	Complete. No IMF period.	Guinea-Bissau	3x3 (CPI Trade Res). Only IMF period
Bhutan	3x3 (CPI RES X). NO IMF period.	Guyana	3x3 (CPI RES X)
Bolivia	Complete.	Haiti	3x4 (CPI Trade Res X). Only IMF period. period
Bosnia Herzegovina	3x3 (R RES X)	Honduras	3x2 (CPI RES). Only IMF period
Botswana	3x3 (CPI RES X). NO IMF period.	Hungary	Complete.
Brunei	3x4 (GDP CPI RES X). No IMF period.	Iceland	Complete.
Bulgaria	Complete.	India	Complete. IP instead of GDP
Burundi	3x4 (CPI TRADE RES X)	Indonesia	3x4 (GDP CPI Trade R)
Cape Verde	3x3 (CPI RES X)	Iran	3x2 (GDP CPI). No IMF period.
Cambodia	3x3(CPI TRADE RES)	Ireland	Complete. IP instead of GDP
Cameroon	3x3(CPI TRADE RES)	Israel	Complete.
Canada	Complete. NO IMF period.	Italy	Complete. No IMF period.
Chad	3x2 (CPI RES). Only IMF period	Jamaica	Complete.
Chile	Complete. Unemployment instead of GDP	Japan	Complete. NO IMF period.
China	3x3 (GDP CPI X)	Jordan	3x3 (IP CPI Trade)
Colombia	Complete. No IMF period.	Kazakhstan	Complete.
Comoros	3x3 (CPI RES X)	Kenya	Complete. Only IMF period
Congo Democratic	3x2 (CPI Trade)	Korea, Republic of	3x4 (GDP CPI Trade R)
Congo Republic	3x2 (CPI TRADE RES). Only IMF period	Kuwait	3x2 (CPI Res) No IMF period..
Costa Rica	Complete.	Kyrgyz	Complete. Only IMF period
Cote d'Ivoire	3x4 (IP CPI R RES)	Lao	3x2 (CPI RES). Only IMF period
Croatia	Complete.	Latvia	3x4 (GDP CPI Trade R)
Cyprus	3x4 (IP CPI RES X)	Lebanon	3x3 (Trade Res X)
Czech Rep	Complete. NO IMF period.	Lesotho	3x4 (CPI R RES X). Only IMF period
Denmark	Complete. NO IMF period.	Liberia	3x4 (CPI R RES X). Only IMF period
Djibouti	3x2 (Trade Res). Only IMF period	Libya	3x4 (GDP Trade Res X). No IMF period
Ecuador	3x4 (GDP CPI Trade RES)	Lithuania	3x4 (GDP CPI Trade R)

[1] 3x2 means the model has 3 external shocks and 2 domestic variables. Res = Reserve; R = Interest rate; X= Exchange rate; IP= Industrial production;

Country-model list

Country	Model	Country	Model
Luxembourg	3x4 (GDP CPI Trade X). No IMF period.	Serbia	3x2 (GDP CPI). Only IMF period
Macedonia	3x3 (IP CPI RES)	Seychelles	3x3 (CPI Res X)
Madagascar	3x3 (CPI Trade Res). Only IMF period.	Sierra Leone	3x3 (CPI Trade Res)
Malawi	Complete. Only IMF period	Singapore	3x4 (GDP CPI Res X). No IMF period.
Malaysia	Complete. No IMF period	Slovak Republic	Complete.
Maldives	3x3 (CPI Res X)	Slovenia	Complete.
Mali	3x2 (CPI RES). Only IMF period	Solomon Islands	3x3 (CPI R Res)
Malta	Complete. NO IMF period.	South Africa	Complete.
Mauritania	3x2 (CPI X). Only IMF period	Spain	Complete.
Mauritius	Complete. NO IMF period.	Sri Lanka	Complete. Only IMF period
Mexico	Complete.	St Kitts and Nevis	3x2 (CPI Res). Only IMF period
Micronesia	3x2 (R RES). No IMF period.	St. Lucia	3x2 (CPI Res). Only IMF period
Moldova	Complete. Only IMF period	St. Vincent	3x2 (CPI Res). Only IMF period
Mongolia	3x4 (CPI Trade R Res). Only IMF period	Sudan	3x4 (CPI Trade Res X). Only IMF period
Morocco	Complete.	Suriname	3x4 (CPI Trade Res). No IMF period.
Mozambique	3x4 (CPI Trade Res X). Only IMF period	Swaziland	3x3 (CPI Res X)
Myanmar	3x3 (CPI Trade Res)	Sweden	Complete. NO IMF period.
Namibia	Complete. NO IMF period.	Switzerland	Complete. NO IMF period.
Nepal	3x3 (CPI Trade Res)	Syria	3x2 (IP CPI). No IMF period.
Netherlands	Complete. No IMF period.	Tajikistan	3x4 (CPI R RES X). Only IMF period
New Zealand	Complete. No IMF period.	Tanzania	3x4 (GDP CPI R Res). Only IMF period
Nicaragua	Complete. Only IMF period	Thailand	Complete.
Niger	3x2 (CPI Res). Only IMF period.	The Gambia	3x4 (CPI Trade Res X)
Nigeria	Complete. NO IMF period.	Timor-Leste	3x3 (CPI R Res). No IMF period.
Norway	Complete. NO IMF period.	Togo	3x2 (CPI Res). Only IMF period
Oman	Complete. NO IMF period.	Tonga	3x3 (CPI R Res). No IMF period.
Pakistan	Complete. Only IMF period	Trinidad and Tobago	3x4 (IP CPI R X)
Panama	3x3 (IP CPI Res)	Tunisia	Complete.
Paraguay	3x3 (IP CPI Res). NO IMF period.	Turkey	Complete.
Peru	Complete.	Uganda	3x4 (CPI Trade R Res). Only IMF period
Philippines	Complete.	Ukraine	Complete. Only IMF period
Poland	Complete.	United Arab Emirates	3x4 (IP Trade Res X). No IMF period.
Portugal	Complete.	United Kingdom	Complete.
Qatar	3x4 (IP CPI Trade X). No IMF period.	Uruguay	Complete.
Romania	Complete. Only IMF period	Vanuatu	3x4 (CPI R Res X). No IMF period.
Russia	Complete.	Venezuela	3x4 (IP CPI Trade X)
Rwanda	3x2 (CPI RES). Only IMF period	Vietnam	3x3 (IP CPI R). Only IMF period
Samoa	3x3 (CPI Trade Res)	Yemen	3x4 (CPI R Res X). Only IMF period
San Marino	3x2 (CPI RES). NO IMF period.	Zambia	3x3 (CPI Trade X). Only IMF period
Sao Tome and Principe	3x3 (CPI R Res). Only IMF period		
Saudi Arabia	Complete. No IMF period.		
Senegal	3x3 (IP CPI RES). Only IMF period		

Figure S1: Vulnerability to external shocks and participation in IMF programs- Cholesky decomposition

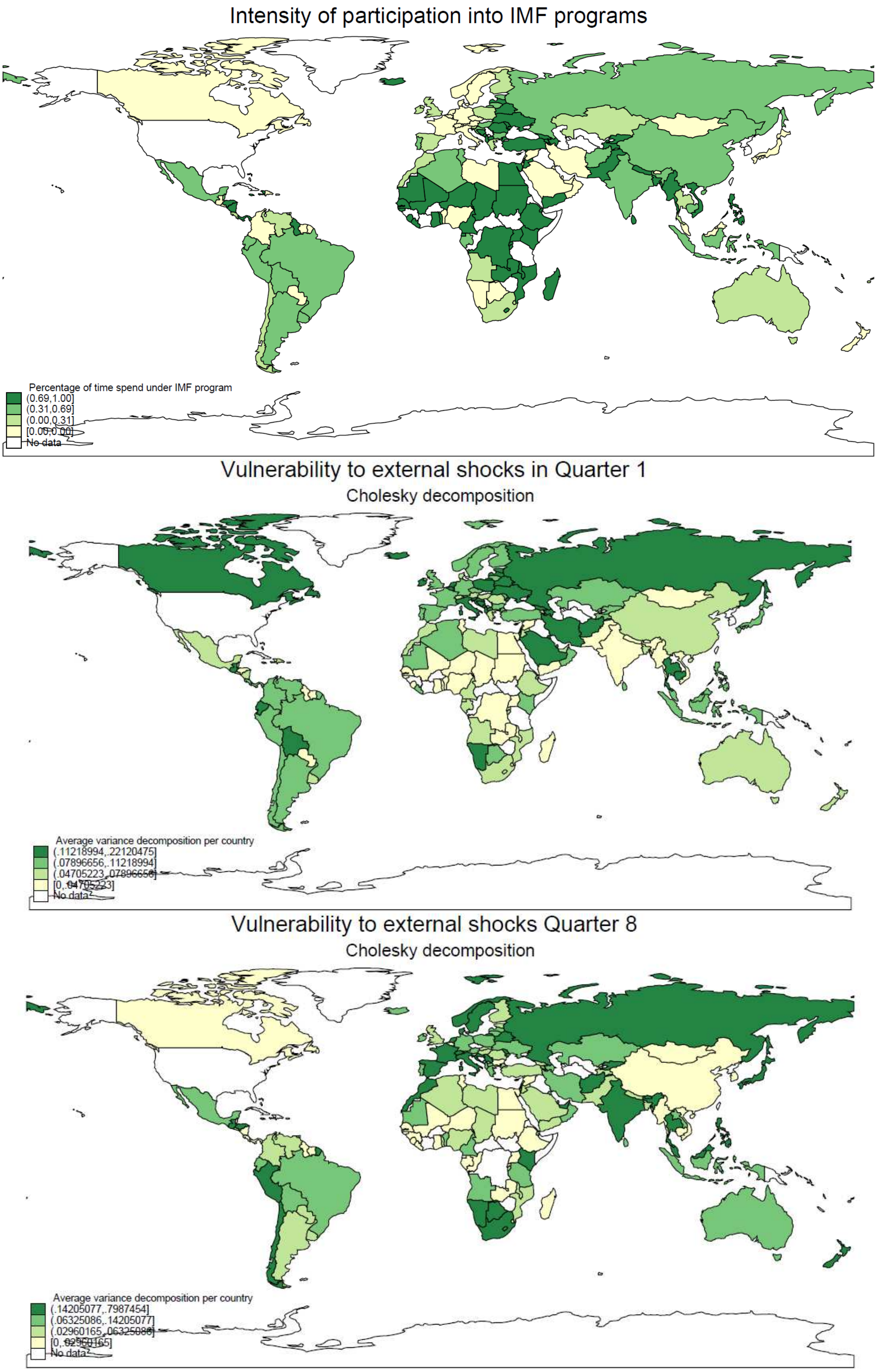


Figure S2: Vulnerability to external shocks and participation into IMF programs- World shocks

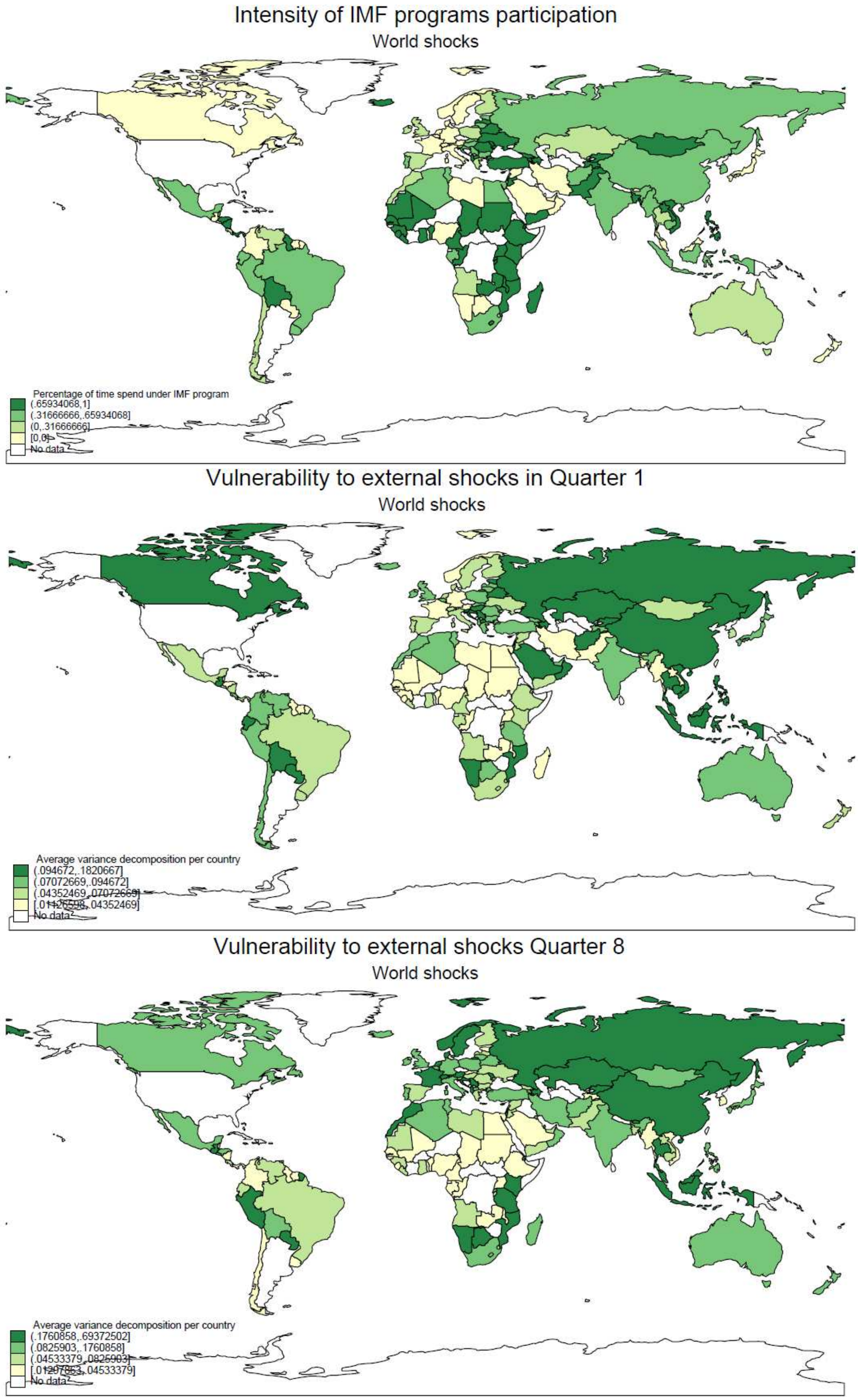


Table S1: World IV results

VARIABLES	(First stage) IMF	(Q1) Vulnerability	(Q8) Vulnerability	(Q40)
IMF		-0.908	-2.272	-2.135
		(0.970)	(1.541)	(1.515)
KOpen	-0.00353***	0.00138	-0.00391	-0.00356
	(0.000857)	(0.00396)	(0.00677)	(0.00665)
logFDI	0.0824*	0.199*	0.302	0.297
	(0.0445)	(0.120)	(0.224)	(0.216)
logTrade	0.0243	-0.0656	0.0575	0.0493
	(0.0376)	(0.0553)	(0.0922)	(0.0887)
logGDP	-0.0224	0.0377	-0.0527	-0.0533
	(0.0313)	(0.0488)	(0.105)	(0.101)
IMFquota	-0.0668**			
	(0.0320)			
Constant	0.649**	-2.887***	-1.773*	-1.873**
	(0.274)	(0.599)	(0.955)	(0.941)
Observations	157	157	157	157
R-squared	0.173			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(First stage) IMFintensity	(Q1) Vulnerability	(Q8) Vulnerability	(Q40) Vulnerability
IMFintensity		-0.684	-1.711**	-1.607**
		(0.564)	(0.795)	(0.793)
KOpen	-0.00324***	0.00237	-0.00144	-0.00124
	(0.000715)	(0.00228)	(0.00389)	(0.00387)
logFDI	0.0623	0.167**	0.222	0.221*
	(0.0414)	(0.0696)	(0.136)	(0.131)
logTrade	0.0547*	-0.0502	0.0959	0.0855
	(0.0312)	(0.0496)	(0.0942)	(0.0922)
logGDP	0.0120	0.0662*	0.0188	0.0139
	(0.0310)	(0.0392)	(0.0945)	(0.0910)
IMFquota	-0.0887***			
	(0.0254)			
Constant	0.237	-3.315***	-2.842***	-2.877***
	(0.223)	(0.286)	(0.565)	(0.553)
Observations	157	157	157	157
R-squared	0.240	0.171		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table S2: OLS results. Model heterogeneity

Real activity vulnerability

VARIABLES	(Q1) Real activity (log)	(Q8) Real activity (log)	(Q40) Real activity (log)
IMFIntensity	-0.0716	-0.460*	-0.466*
	(0.215)	(0.277)	(0.249)
KOpen	0.00437	0.00137	0.00129
	(0.00305)	(0.00388)	(0.00365)
logGDP	0.145*	0.117	0.0797
	(0.0829)	(0.106)	(0.0964)
logTrade	-0.0168	0.00496	0.00879
	(0.0865)	(0.0924)	(0.0815)
logFDI	0.0331	-0.0283	0.0343
	(0.0641)	(0.0970)	(0.0815)
Constant	-3.366***	-2.571***	-2.775***
	(0.465)	(0.584)	(0.523)
Observations	101	101	101
R-squared	0.069	0.052	0.055

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Complete model

VARIABLES	(Q1) Vulnerability	(Q8) Vulnerability	(Q40) Vulnerability
IMFIntensity	-0.0599	-0.467*	-0.489**
	(0.116)	(0.254)	(0.245)
KOpen	0.00332**	0.00130	0.00132
	(0.00164)	(0.00364)	(0.00355)
logGDP	0.0207	0.0933	0.0762
	(0.0473)	(0.0979)	(0.0934)
logTrade	-0.0684	0.00554	0.0101
	(0.0428)	(0.0830)	(0.0789)
logFDI	0.0836**	0.00361	0.0437
	(0.0370)	(0.0823)	(0.0813)
Constant	-2.795***	-2.665***	-2.816***
	(0.249)	(0.521)	(0.503)
Observations	101	101	101
R-squared	0.121	0.055	0.062

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Chapter 2

S2 Sensitivity analysis

In this section we test the robustness of our results to the followings: the specification of the transition function, the identification strategy, the real activity variable, the size of shocks, the inflation variable, the threshold variable definition and the tightness of priors.

S2.1 Sensitivity to the transition across regimes function

It has been mentioned previously that TVAR imposes fairly stringent restrictions on the relation between the threshold variable and transition across regimes since the threshold variable is assumed to cause the shift across regimes in a deterministic way.

As an alternative to the TVAR, in this section we replicate the empirical exercise using a Smooth Transition VAR (STVAR) defined as in (2.8), (2.9) and (2.10). We therefore relax the assumption of a deterministic switch in regimes and we allow for a gradual transition between good and bad times. However, we do not account for the heteroskedasticity as we consider a unique covariance matrix.

The results of the STVAR model (Figures S4-S7) are similar to the TVAR results. The difference in the global connectedness index over the business cycle phases is even more pronounced than in the TVAR case, going from 20% in the benchmark specification to 30% in the inflation specification. When only IP variables are considered, negative shocks are found to trigger higher spillover effects than positive shocks. No sign asymmetry is detected when we include financial variables. Overall, the results regarding the global connectedness are qualitatively in line with to the ones obtained with the benchmark model, with some variation mainly in the composition of the global index.

S2.2 Sensitivity to the identification strategy

The generalized identification used in the baseline analysis allows for correlated shocks; as such, in order to validate our results in this section we repeat the empirical application using the Cholesky decomposition to orthogonalize the system. With the recursive identification, the order of the variables needs some additional consideration[2]. The ordering of the variables across countries follows the same ranking used in defining the threshold variable; we start with US followed by Japan, UK, Germany, France, Italy and Spain. In the two alternative specifications real variables come before financial variables while we choose to put inflation before the real activity variable (Primiceri, 2005).

The results obtained with the Cholesky decomposition (Figures S8-S11) are qualitatively similar to the benchmark analysis, with a slightly smaller magnitude of the directional results.

S2.3 GDP connectedness

In this subsection we calculate the GDP connectedness for the seven countries analyzed. We use year to year log growth rates of quarterly GDP (seasonal adjusted), from 1961 Q1 to 2015 Q4. We adjust the number of lags accordingly from 13 to 4 and we limit the values of the delay parameter from 1 to 4 in order to be consistent with the benchmark approach. The results of this alternative specification reported in Figure S12 are in line with the findings of the baseline model confirming the robustness of the state-dependent behavior of the global connectedness. Moreover, the difference in the GDP global connectedness index over the business cycle phases is significantly higher than the one obtained for the IP suggesting that the GDP variable is more connected than the IP.

S2.4 Sensitivity to the size of shocks

When measuring connectedness following big shocks, 10 standard deviation shocks were employed. In order to test the sensitivity of our estimates to the size of the shock, in Figure S16 results based on 5 standard deviation shocks are reported. Conclusions from the baseline specifications are robust to this test.

S2.5 Sensitivity to the threshold variable definition

US has a largest weight in the threshold variable and this might raise concerns on the sensitivity of results showing the importance of US as a shock transmitter. In order to check whether the US dominance in the threshold variable has an influence on the robustness of the directional results we run the following robustness analysis: we identify the states of the economy solely based on Germany and then we estimate the directional results and the importance of German shocks to US and US shocks to Germany. Figure S19 reports the directional results based on this new definition of the threshold and shows that results are

[2] Diebold and Yilmaz (2014) claim that often total connectedness is robust to ordering, i.e the range of the total connectedness estimates across orderings is quite small

little affected by this adjustment in the threshold variable. Table S4 as expected, highlights the little relevance of German shocks on US IP and the high importance of US shocks on German IP regardless of the threshold variable definition.

S2.6 Alternative specification of the inflation variables.

S2.7 Model comparison via DIC

We carry out a model selection analysis via the Bayesian deviance information criterion (hereafter DIC) and we compare the performance of the benchmark model against the linear VAR and the STVAR.

Even if Bayes Factors have been considered for many years as the preferred way to conduct Bayesian model comparison, they have come under increasing criticism (Gelfand, 1996). In particular, when the parameter space is large their estimation requires high-dimensional integration which can pose a big computational challenge; moreover they are not well defined when using improper priors and may exhibit problems connected with the "Lindley paradox". As mentioned in Gelfand (1996), if the prior is proper but sufficiently diffuse, it can result in support for the reduced model in spite of the fact that data might suggest its rejection. The Bayes factors tend to give too much weight on model parsimony. That is relevant in our application for two reasons. First, our prior is weakly informative for the threshold variable Z^* and is flat for the delay parameter d. Gelfand (1996) recommends against the use of Bayes factors in this case. Second, the TVAR is by far more complex than the linear VAR[3] and marginal likelihood methods might erroneously prefer the reduced model even if data points to its rejection.

An alternative to the use of Bayes Factors are the penalized likelihood criteria, namely Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and DIC, which penalizes the model complexity and rewards the fit to the data. DIC was introduced in Spiegelhalter et al. (2002) and is a generalization of the AIC. DIC is defined as:

$$DIC = \bar{D} + p_D \tag{5.1}$$

The first term is $\bar{D}$=E(-2lnL(Ψ_i))=$\frac{1}{M}\Sigma_i(-2lnL(\Psi_i))$ and L(Ψ_i) is the likelihood evaluated at the draws of all of the parameters Ψ_i in the MCMC chain. $\bar{D}$ is the posterior expectation of the deviation and it captures the fit of the model. The second term, known as the effective number of parameters, measures the model complexity and is defined as p_D=$\bar{D}$−D($\bar{\Psi}$). p_D can be approximated by $p_D = \frac{1}{M}\Sigma_i(-2lnL(\Psi_i))$-$\big(-2lnL(\frac{1}{M}\Sigma_i\Psi_i)\big)$. Hence, DIC estimation is straightforward and requires only the evaluation of the likeli-

[3]The number of parameters in TVAR is more than double compared to the linear VAR

Table S3: Model comparison via DIC for linear VAR, STVAR and TVAR. Model with smaller DIC is preferred

Model	p_D	$\bar{D}$	DIC
TVAR (benchmark model)	214	5607	6037
STVAR	164	5725	6055
VAR (linear)	148	5769	6065

hood function for each Gibbs-sampler saved draw and for the posterior mean.

It is worth mentioning that with prior distribution, the number of parameters (as in AIC and BIC) do not necessary represent the model complexity. DIC avoids this problem with the use of p_D which is shown to asymptotically approximate the true number of parameters (Spiegelhalter et al., 2002).

Since we want models with good fit but also with a reasonable degree of parsimony, we prefer models with smaller values of DIC. Moreover, DIC is scale-free, so as with AIC and BIC, only differences in DIC across models are meaningful.[4]The simplicity, general applicability and attractive interpretations, led to the broad use of DIC by the data analysts.

Table S3 presents the estimated DIC for the TVAR , STVAR and linear VAR models and provides evidence that our benchmark model is preferred to the linear VAR and the STVAR. As expected, the effective number of parameters increases with the model complexity while for $\bar{D}$, the goodness of fit term, we observe the opposite effect.

S2.8 Threshold vs Markov-switching models

TVAR, STVAR and Markov-switching VAR (hereafter MSVAR) are all regime-switching models. The first two are "threshold" models while the MSVAR is part of the "Markov-switching" models. The main difference between these two categories consists in how they approach the evolution of the state variable S_t. If threshold models assume that regimes switch is driven by the level of an observed variable in relation to an unobserved threshold level, the MS models impose that regime-shifts evolve according to a Markov chain. In particular a two regimes MSVAR can be defined as:

$$Y_t = c_{S_t} + \sum_{j=1}^{P} B_{j,S_t} Y_{t-j} + \Omega_{S_t}^{1/2} e_t \tag{5.2}$$

where $e_t \sim \mathrm{N}(0,\mathrm{I}_N)$ and S_t follows a first order Markov Chain, hence S_t depends only on S_{t-1}. The estimation of 5.2 does not necessarily lead to identification of recessions and expansions as regimes. Hence it is less appropriate to our aims. However, there are several extensions of the MS models which have been used to identify the phases of

[4] p_D does have a scale, i.e. the size of the effective number of parameters.

the business cycle or to allow the probability of switching to depend on some underlying economic fundamentals. In particular, Diebold, Lee, and Weinbach (1994) and Filardo (1994) consider time-varying probabilities in Markov-switching models.

For example, in a two regimes MS model with only one leading indicator z_{t-1} (for simplicity), the time-varying probabilities mechanism can be conveniently expressed with the probit parameterisation as follows:

$$p(s_t = 1 \mid s_{t-1} = i, y_{t-1}, z_{t-1}, \theta) = p_{1j,t} \tag{5.3}$$

$$= \phi(\gamma_i^{'} z_{t-1}) \tag{5.4}$$

where ϕ refers to the c.d.f. of the standard normal distribution and γ_i measures the sensitivity of probability $p_{ij,t}$ with respect to the indicator variable z_{t-1}.

Even if the model described in 5.2 - 5.4 can be easily adapted to the objectives of our analysis, it has two main drawbacks. First, if the sample considered includes few transitions across different regimes (which is the case in our application), the estimation of the parameters determining the transition probabilities can be extremely problematic. One solution to this issue is to impose very informative priors on these parameters at the cost of obtaining posterior distributions not dominated by data evidence (Amisano and Fagan, 2013). Second, the estimation of an MS model with time-varying probabilities is highly complex.

Finally, threshold and Markov-switching approaches should be viewed as complementary and the "preferred" model is likely to be specific to the application itself. For the reasons mentioned above, we consider the TVAR model to be more appropriate for our application.

S3 Convergence of the Markow chain Monte Carlo algorithm

This appendix assesses the convergence of the Markow chain Monte Carlo algorithm in the baseline application to the IP data. For the TVAR model estimation we employ 20,500 iterations of the Gibbs sampler discarding the first 20,000 as burn-in.[5] In order to check the convergence of the Gibbs sampler we follow Primiceri (2005) and we apply the Inefficiency factors (IFs) for the posterior estimates of the parameters. The IF is the inverse of the relative numerical efficiency measure proposed by Geweke's (1992). Specifically, the IF is

[5]We save only 500 draws becuase the Generalized Impulse Response Functions are computationally intensive and time cosuming.

an estimate of $\left(1+2\sum_{k=1}^{\infty}\rho_k\right)$ where $\sum\rho_k$ is the k-th autocorrelation of the chain. Values of the IFs below or around twenty are considered satisfactory. Figure S17 presents the IFs for the different sets of parameters. The IFs for the threshold level is 10.5 while for all the other parameters the IFs are below 10. Therefore the convergence diagnostics seem satisfactory.

S4 Mixed-variables model and aggregation of the connectedness table.

The results based on the mixed-variable model reported in section 5.2 rely on the introduction of an intermediate level of aggregation in the spirit of Greenwood-Nimmo et al., (2015). The mixed specifications combine IP variables with financial or nominal variables; therefore the final model features N=14 endogenous variables[6]. Given our interest in analyzing the real, financial and nominal connectedness across business cycle phases, the aggregation scheme we adopt is based on the type of variable and is well described by the following steps:.

Step 1. Split the 14x14 forecast error variance decomposition (FEVD) matrix in 4 as follows:

$$C=\begin{bmatrix} RR & FR \\ RF & FF \end{bmatrix} \tag{5.5}$$

where each element of the C matrix is a 7x7 sub-matrix containing specific pieces of variance decomposition. For example, RF is made up of the shares of the forecast error variation in financial variables explained by shocks to real variables.

Step 2. Sum the elements of each sub-matrix and subtract its trace (sum of the elements on the main diagonal). Note that the main diagonals of RR and FF coincide with the main diagonal of the C matrix. In order to have a clean cross-countries spillover index, the traces of RF and FR matrices are also subtracted since they account for effects of domestic shocks on another domestic variables (for example the effect of US IP shock on US SPI variable).

Step 3. Divide by N the sub-indexes to restore the percentage interpretation.

Step 4. Report the global index as sum of the 4 sub-indexes.

[6]Given la large number of parameters in the mixed-variables model, the number of lags were reduced to 8

Table S4: Forecast error variance decomposition for US and Germany shocks with regimes identified solely based on Germany.

	Recession			Boom	
Variable\Shock	US	Germany	Variable\Shock	US	Germany
US 1 Year	0.7958	0.0155	US 1 Year	0.8356	0.007
Germany 1 Year	0.1571	0.5021	Germany 1 Year	0.10	0.6355
US 5 Years	0.6922	0.0404	US 5 Years	0.7624	0.0245
Germany 5 Years	0.1613	0.4114	Germany 5 Years	0.1390	0.5134

To help fix ideas we report a simple example for a model with two countries (US and UK) and two variables per country (IP and SPI). Suppose the FEVD matrix has the following form:

Variable\Shock	IP_US	IP_UK	SPI_US	SPI_UK
IP_US	d_{11}	d_{12}	d_{13}	d_{14}
IP_UK	d_{21}	d_{22}	d_{23}	d_{24}
SPI_US	d_{31}	d_{32}	d_{33}	d_{34}
SPI_UK	d_{41}	d_{42}	d_{43}	d_{44}

where the element d_{11} shows how much of the forecast error variation in IP_ US is explained by shocks in the IP_US variable.

The sub-matrices in 5.5 are then built as follows:

$$\text{RR}= \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}; \text{RF}= \begin{bmatrix} d_{31} & d_{32} \\ d_{41} & d_{42} \end{bmatrix};$$

$$\text{FR}= \begin{bmatrix} d_{13} & d_{14} \\ d_{23} & d_{24} \end{bmatrix}; \text{FF}= \begin{bmatrix} d_{33} & d_{34} \\ d_{43} & d_{44} \end{bmatrix};$$

For each sub-matrix obtain a sub-index calculated as the sum of its off diagonal elements divided by N. For example:

$$RRindex = \tfrac{1}{2}(d_{21} + d_{12}).$$

Finally, the global connectedness index is obtained as the sum of the four sub-indexes, RR, RF, FR, FF.

Figure S3: Median of the difference in global connectedness across regimes over the forecasting horizon. 68% credibility bands.

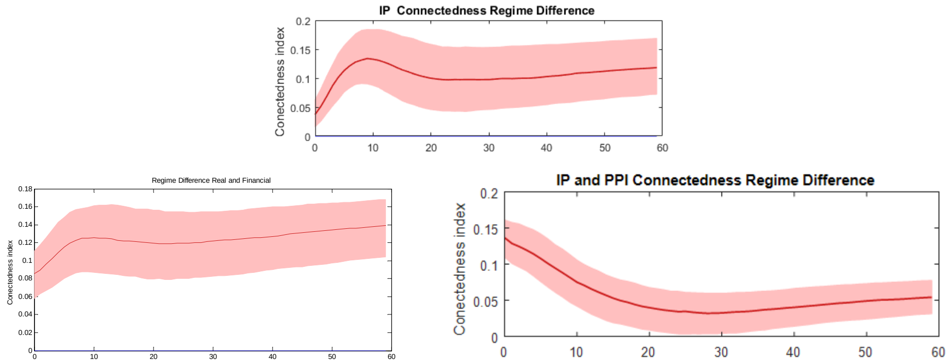


Figure S4: STVAR. Median of the difference in global connectedness across regimes over the forecasting horizon. 68% credibility bands.

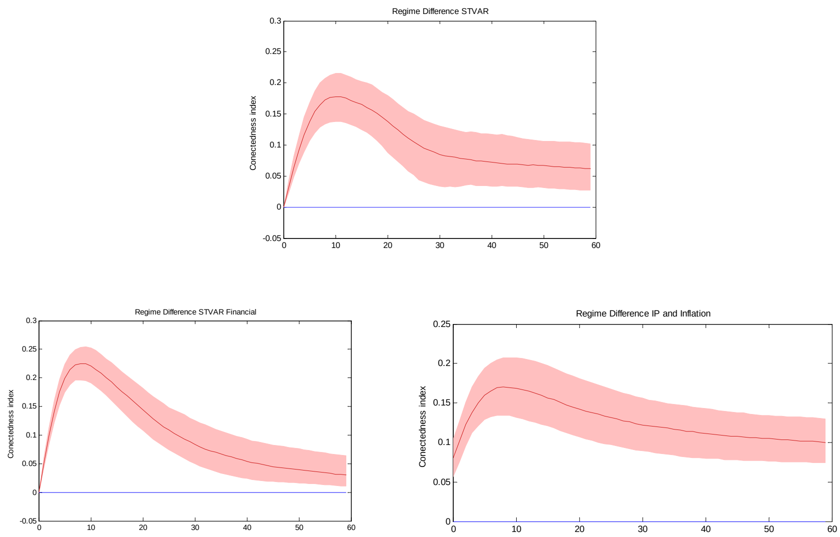


Figure S5: STVAR: IP connectedness

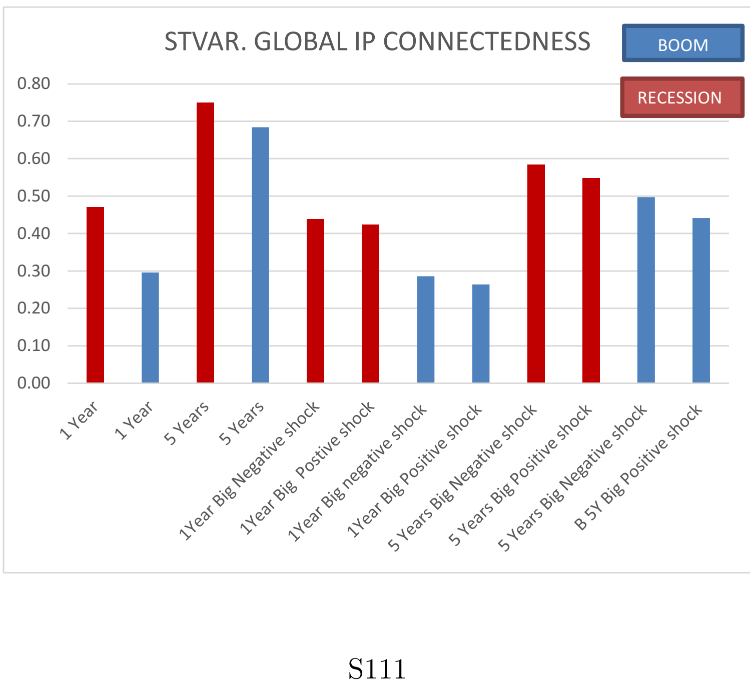


Figure S6: STVAR: Financial and IP connectedness. R and B at the bottom of each bar stays for recession and boom. The RR, RF, FR and FF in the legend indicate the nature of the variables, i.e. real and financial. For example RF means the effects IP shocks have on financial connectedness.

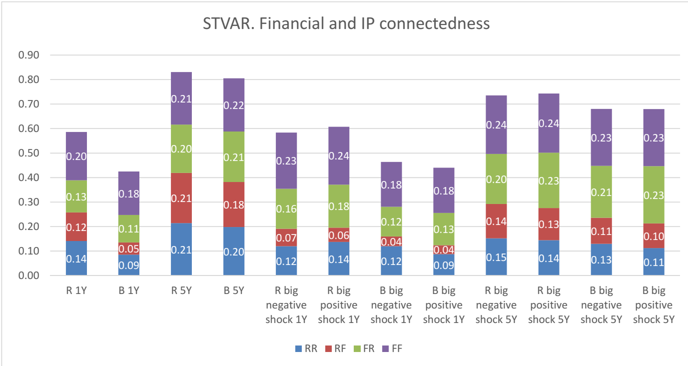


Figure S7: STVAR: Inflation and IP connectedness.R and B at the bottom of each bar stays for recession and boom.

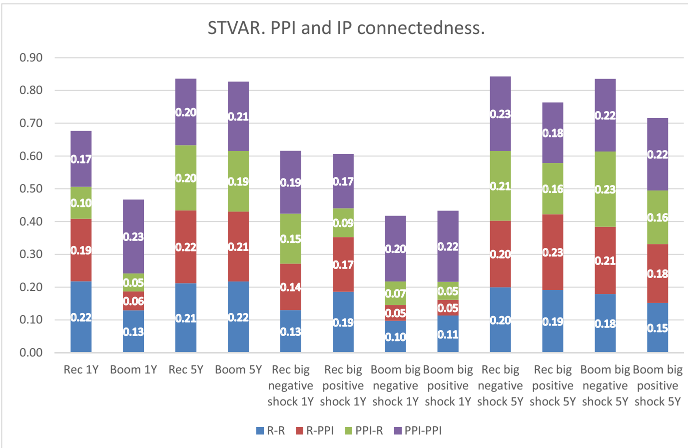


Figure S8: Cholesky decomposition. Median of the difference in global connectedness across regimes over the forecasting horizon. 68% credibility bands.

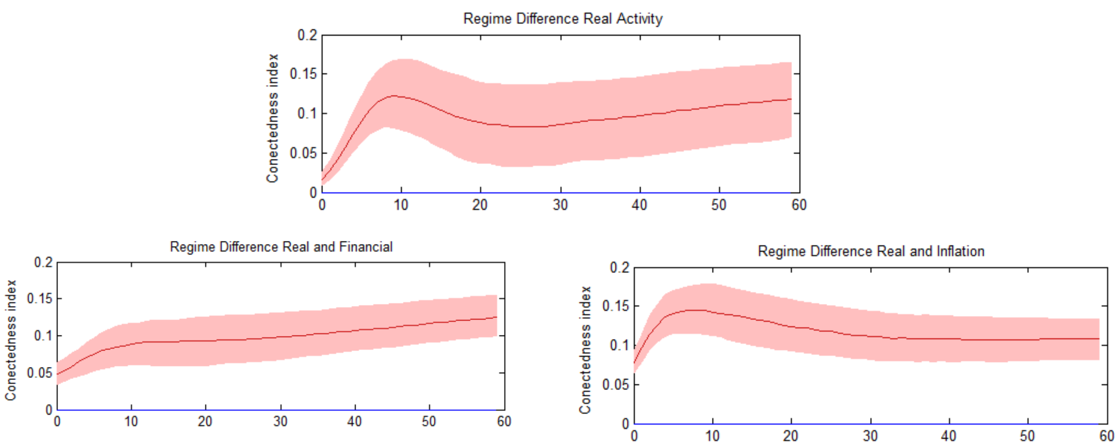


Figure S9: Cholesky decomposition. Global IP connectedness.

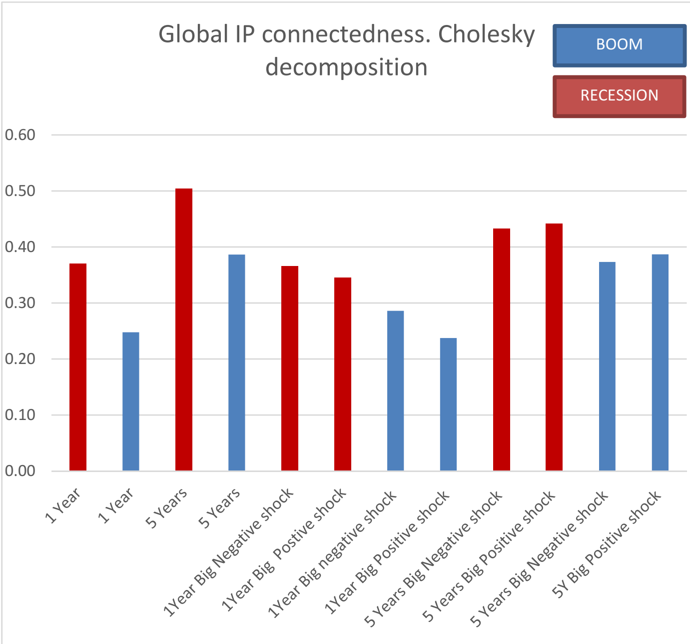


Figure S10: Cholesky decomposition. Financial and IP connectedness. R and B at the bottom of each bar stays for recession and boom. The RR, RF, FR and FF in the legend indicate the nature of the variables, i.e. real and financial.

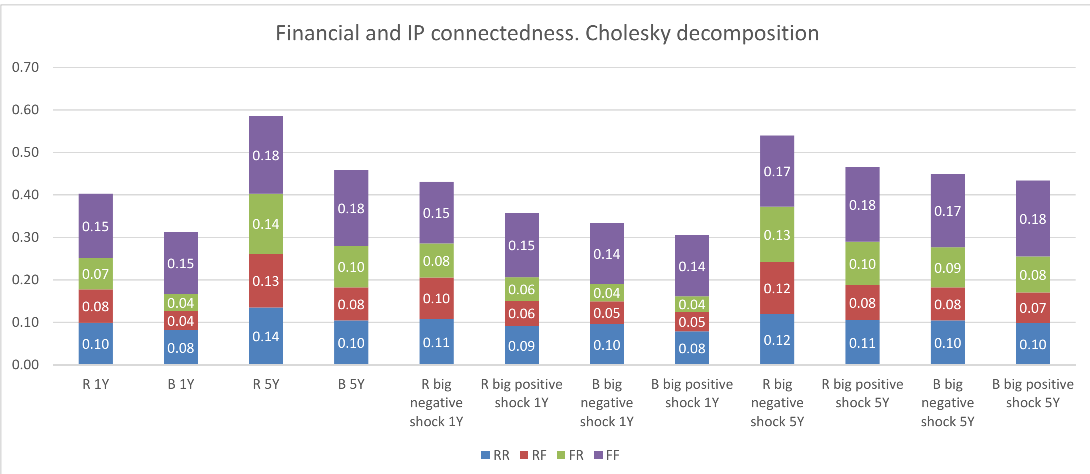
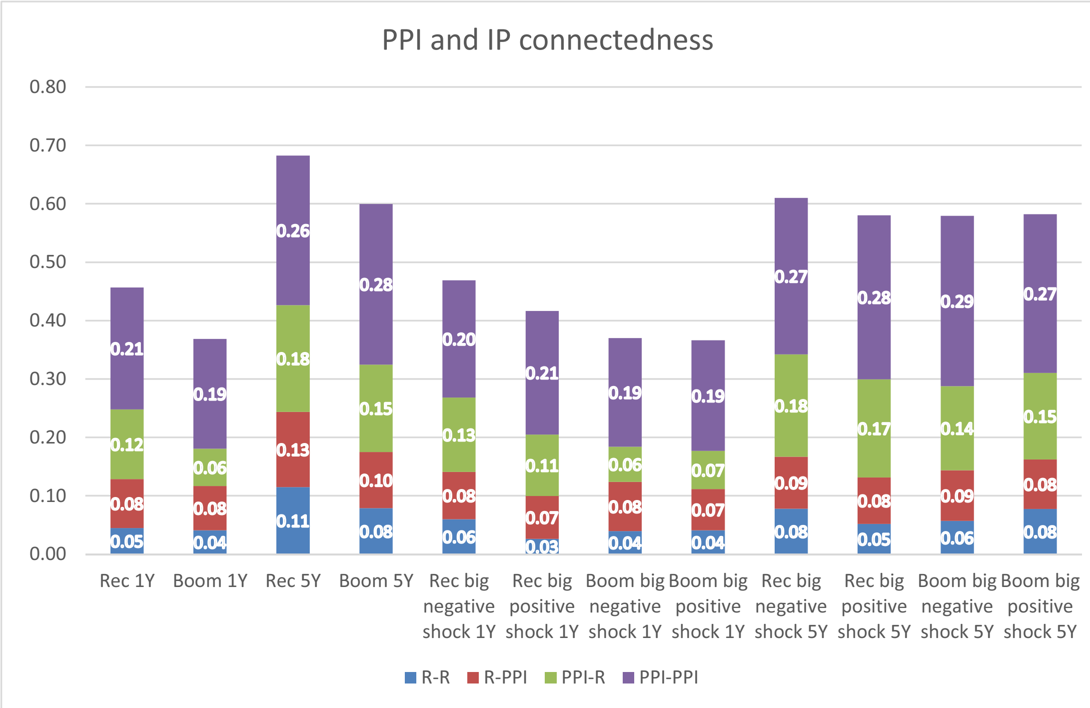


Figure S11: Cholesky decomposition. Inflation and IP connectedness.R and B at the bottom of each bar stays for recession and boom.



Algorithm .1 TVAR model estimation. MH within Gibbs sampling algorithm.

Step 1. Given an initial value for $Z^*$and d, separate the data into two regimes (below and above the threshold).

Step 2. Sample the VAR parameters B_i and Σ_i in each regime i=1,2:

$$P(B_i \mid \Sigma_i, Y_t, Z^*) \sim N(vec(B_i^*), \Sigma_i \otimes (X_i^{*'} X_i^*)^{-1})$$

$$P(\Sigma_i \mid B_i, Y_t, Z^*) {\sim} IW(S_i^*, T_i^*)$$

Step 3. Use a MH step to sample Z*and then compute the acceptance probability α.

$$Z_{new}^* = Z_{old}^* + \Phi^{1/2} e, e{\sim}N(0,1)$$

$$\alpha = \frac{F(Y \mid B_i, \Sigma_i, d_i, Z_{new}^*) p(Z_{new}^*)}{F(Y \mid B_i, \Sigma_i, d_i, Z_{old}^*) p(Z_{old}^*)}$$

where $F(Y \mid B_i, \Sigma_i, Z_{new}^*) p(Z_{new}^*)$ is the likelihood of the VAR computed as the product of the likelihoods in the two regimes. We choose the scaling factor Φ to ensure that the acceptance rate remains between 20% and 40%.

Step 4. Draw the delay parameter d from the multinomial distribution with probability:

$$\frac{L(Y \mid d, \Psi)}{\sum_{d=1}^{n} L(Y \mid d, \Psi)}$$

where L (.) is likelihood function, Ψ denotes all the other parameters and n the maximum value d can take.

Figure S12: GDP global connectedness

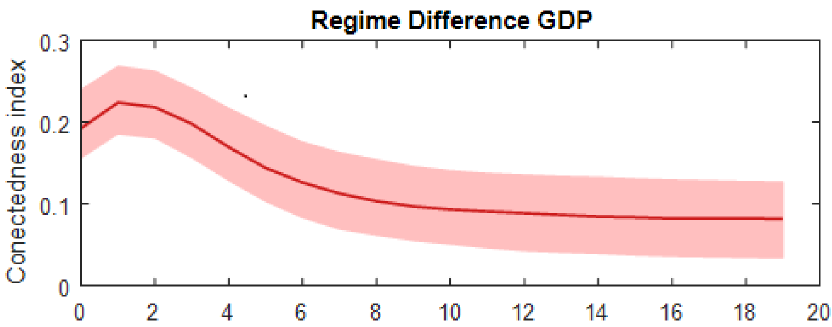


Figure S13: Directional IP results for different shock specifications and horizon

Figure S14: Financial and IP directional connectedness

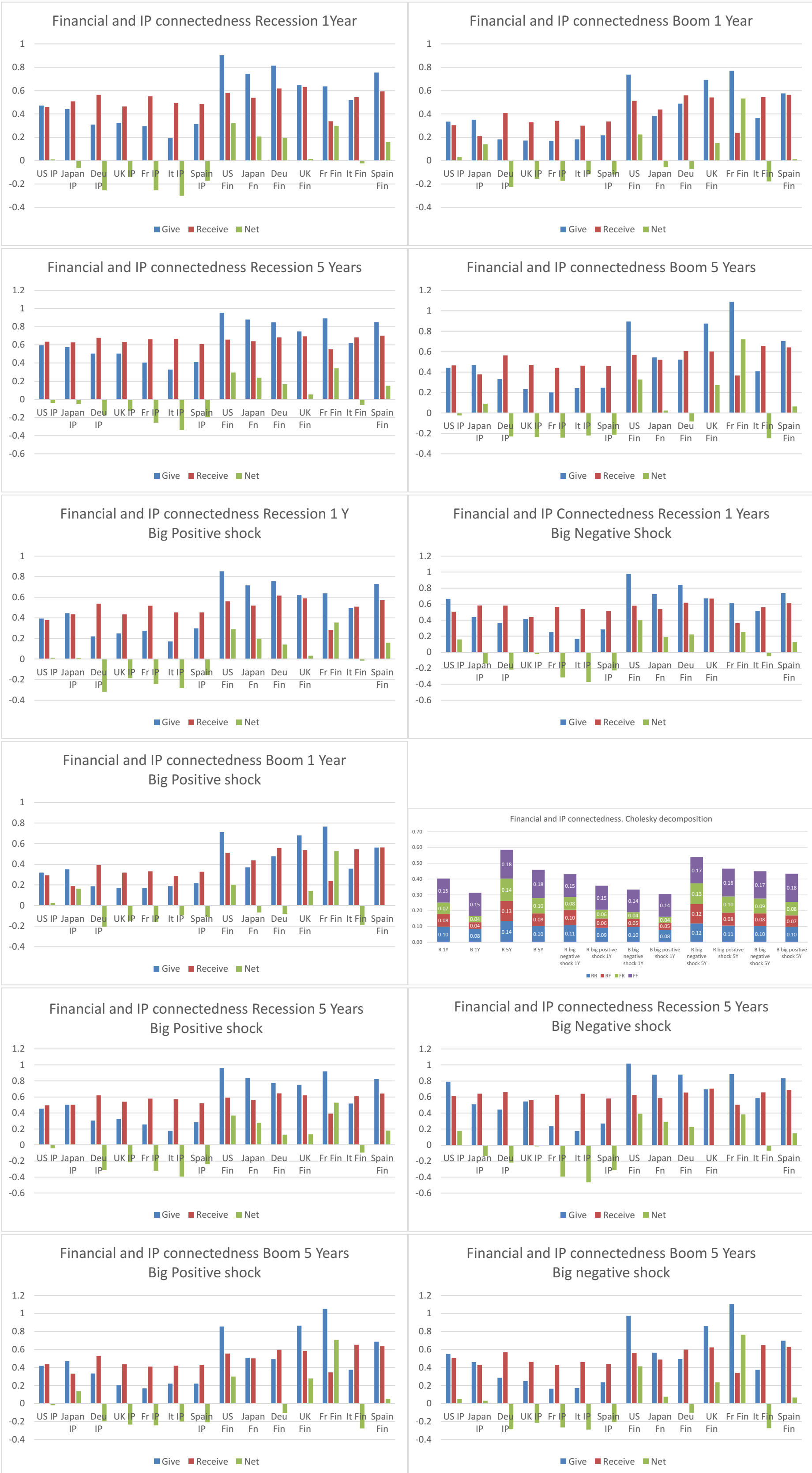
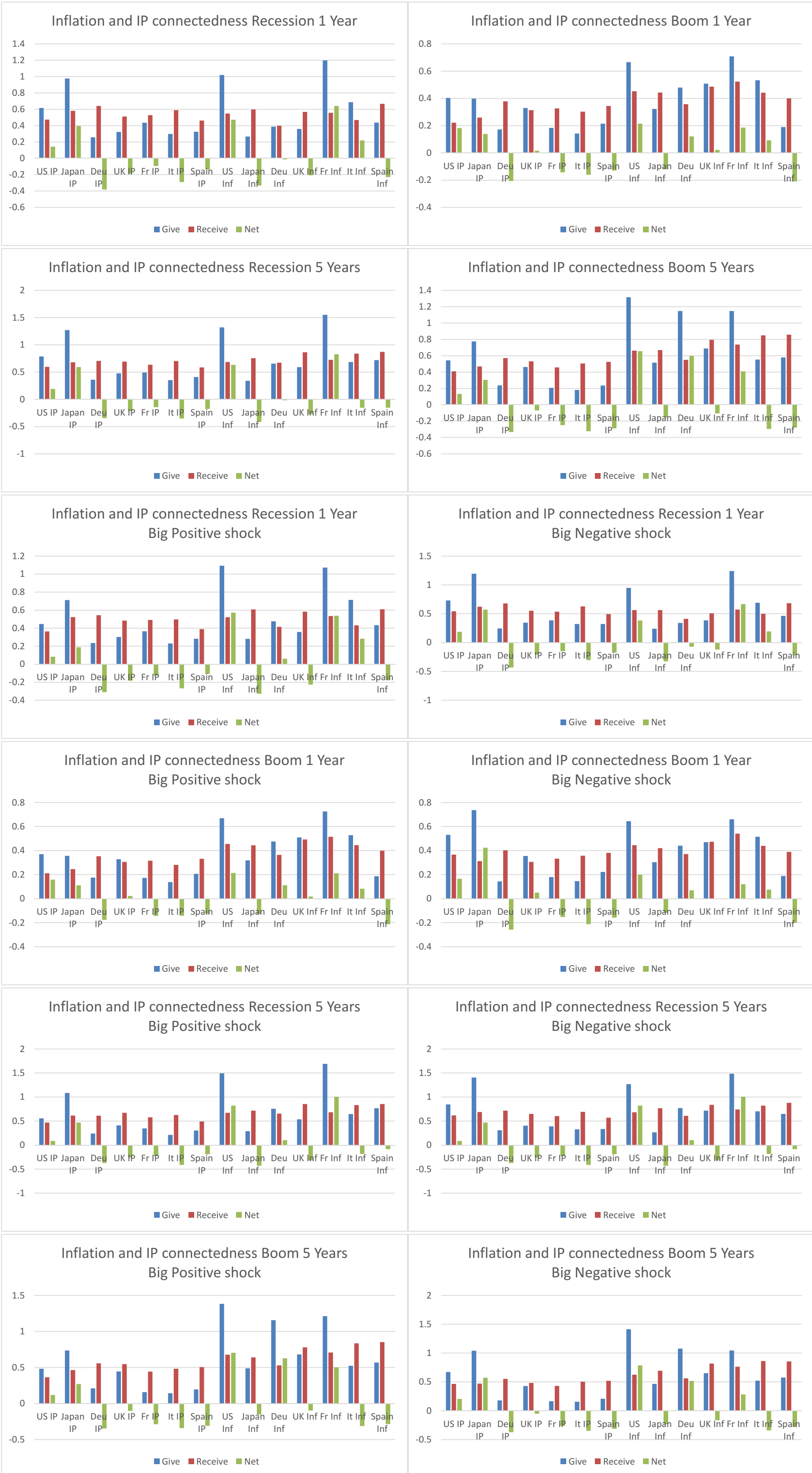


Figure S15: Inflation and IP directional connectedness



Algorithm .2 STVAR model estimation. MH within Gibbs sampling algorithm.

Step 1. Given an initial value for $Z^*$and d, separate the data into two regimes (1-$\pi \lesssim 0.2$).
Step 2. Sample the VAR parameters B_1

$$H(B_1 \mid \Omega, Y_t, Z^*, d) \sim N(vec(B_1^*), \Omega \otimes (X_1^* X_1^*)^{-1})$$

by transforming the model conditional on the parameters of the transition function and regime 2 as:

$$Y_{1t} = B_1 X_t + \varepsilon_t,$$

where Y_{1t}= Y_t-$[B_2 X_t]\pi$;

$$Y_1^* = [Y_{1t}; Y_D]; X_1^* = [X_{1t}; X_D]$$

Step 3. Sample the VAR parameters B_2

$$H(B_2 \mid \Omega, Y_t, Z^*, d) \sim N(vec(B_2^*), \Omega \otimes (X_2^* X_2^*)^{-1})$$

$$Y_{2t} = B_2 X_t \pi + \varepsilon_t$$

where Y_{2t}= Y_t-$[B_1 X_t]$;

$$Y_2^* = [Y_{2t}; Y_D]; X_2^* = [X_{2t}; X_D]$$

Step 4. Sample the VAR parameters B_2

$$H(\Omega \mid B_2, Y_t, Z^{*)} \sim IW(S^*, T^*)$$

Step 5. Use MH to sample P= [Z^*;λ] and then compute the acceptance probability α.

$$P = P_{old} + \Phi^{1/2} e, e \sim N(0,1)$$

$$\alpha = \frac{F(Y \mid B_i, \Omega, d_i, P_{new}) p(P_{new})}{F(Y \mid B_i, \Omega, d_i, P_{old}) p(P_{old})}$$

where $F(Y \mid B_i, \Omega, P_{new}) p(P_{new})$ is the likelihood of the VAR computed as the product of the likelihoods in the two regimes. We choose the scaling factor Φ to ensure that the acceptance rate remains between 20% and 40%.

Step 6. Draw the delay parameter d from the multinomial distribution with probability:

$$\frac{L(Y \mid d, \Psi)}{\sum_{d=1}^{n} L(Y \mid d, \Psi)}$$

where L (.) is likelihood function, Ψ denotes all the other parameters and n the maximum value d can take.

Figure S16: IP connectedness with big shocks of 5 SD

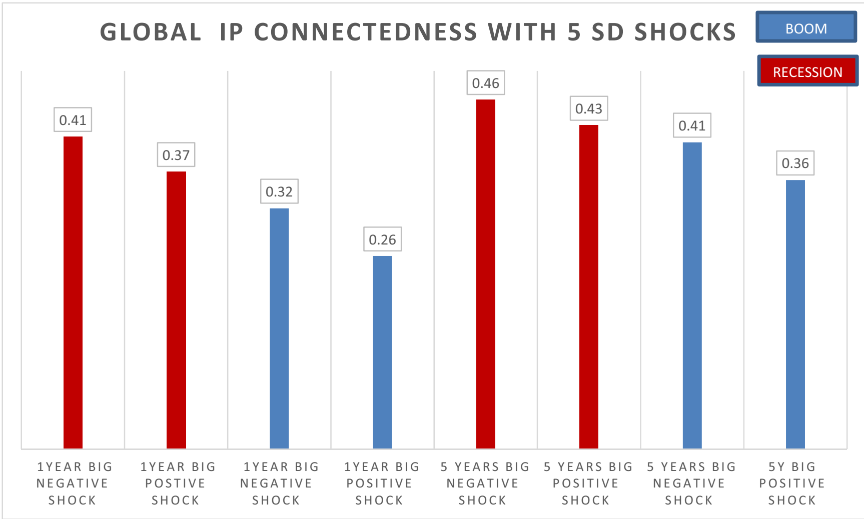


Figure S17: Inefficiency factors.

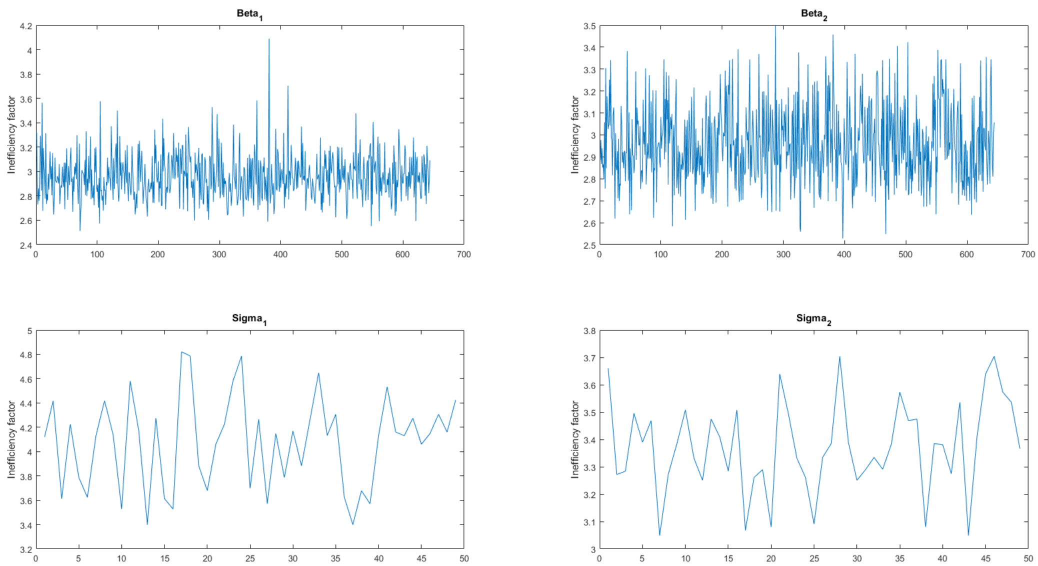


Figure S18: Median of the difference in global connectedness across regimes over the forecasting horizon. 68, 95 and 99% credibility bands.

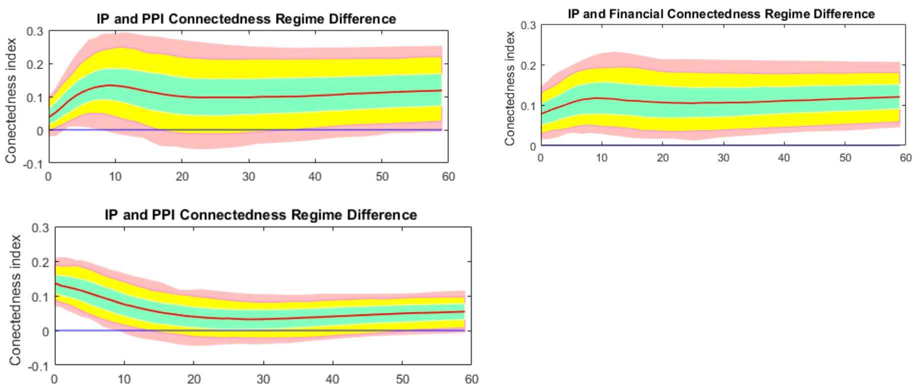


Figure S19: Directional results with regimes identified solely based on Germany.

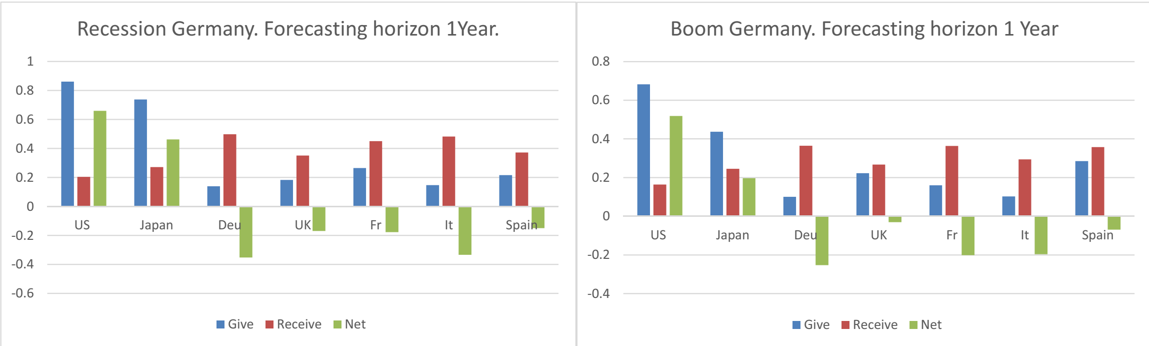


Figure S20: CPI and IP connectedness.

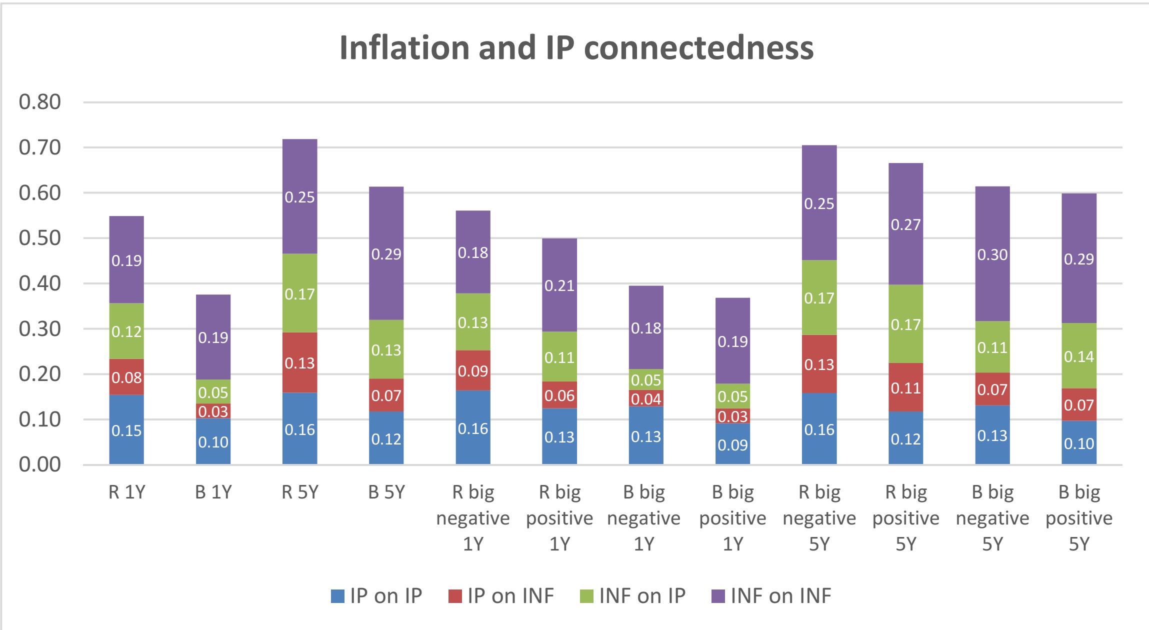
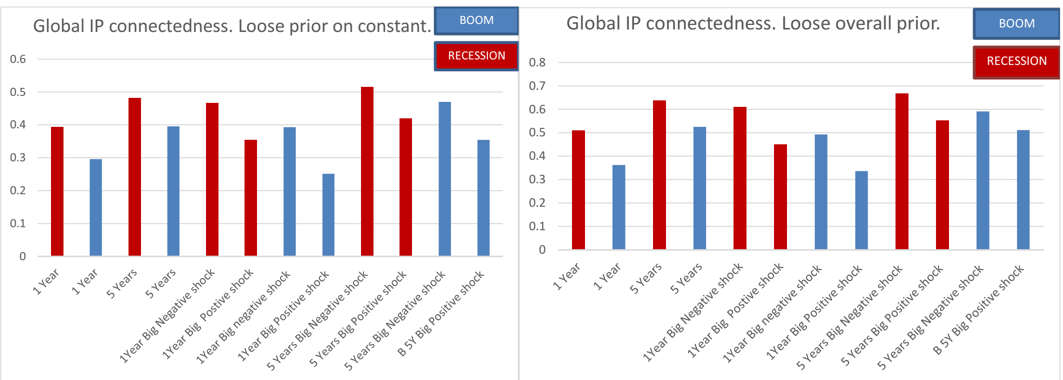


Figure S21: Global connectedness. Sensitivity to prior tightness.



Appendix Chapter 3

Conditional forecast example

Imagine the policymaker wants to answer the following question:

What is the forecast of GDP conditioned on knowing that Federal Fund rate in the next 2 periods is 1%?

Step1. Define a simple 2 variables VAR as in 3.1 formed by GDP (Y) and Interest rate (X).

$$\begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} B_1 & B_2 \\ B_3 & B_4 \end{pmatrix} \begin{pmatrix} Y_{t-1} \\ X_{t-1} \end{pmatrix} + \begin{pmatrix} A_{11} & \\ A_{21} & A_{22} \end{pmatrix} \begin{pmatrix} e_{1t} \\ e_{2t} \end{pmatrix} \tag{6}$$

and define $\mathrm{z}_{ij}{}^k$ as the IRF of j to K shock at horizon i and variable X is constrained to be 1 in the next two periods.

$$R = \begin{pmatrix} z^1_{1,2} & z_{1,2}{}^2 & 0 & 0 \\ z^1_{2,2} & z^2_{2,2} & z^1_{1,2} & z^2_{1,2} \end{pmatrix} \tag{7}$$

$$r = \begin{pmatrix} 1 - \bar{X}_{t+1} \\ 1 - \bar{X}_{t+2} \end{pmatrix} \tag{8}$$

where $\bar{X}$ denotes the unconditional forecast of X and r is the difference between the desired path of the Federal Fund rate and its unconditional forecast.

Step2. Re-write the desired restriction in terms of structural shocks e and the matrix of impulse responses R

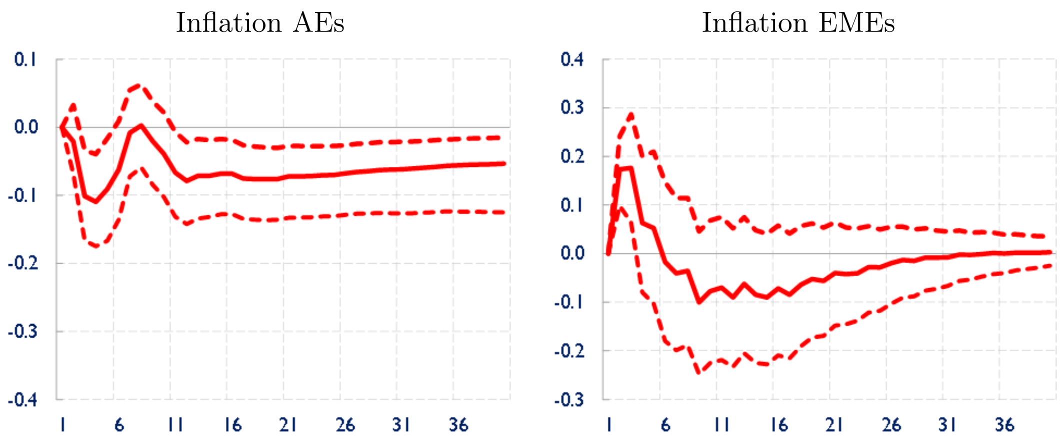
$$Re = r \tag{9}$$

As per Waggoner and Zha (1999) draw the restricted shock e from a distribution:

$$e \sim N\left(R'(RR')^{-1}r,\ I - R'(RR')^{-1}R\right) \tag{10}$$

If we restrict all structural shocks in 9 we get a reduced form solution. If instead we want to attribute the desired path to a specific shock, for example the Monetary policy shock, we draw the restricted shock e_2 from 10 while the remaining shock is drawn from its own distribution which is a N(0,1) in a recursive scenario.

Figure S22: Inflation response to a 1% increase in interest rate. Mean model results



Data description

Data transformations:

- Government spending: Government consumption and government investment deflated by the GDP deflator - annual growth rates.
- Taxes: Current receipts minus transfers and interest payment deflated by the GDP deflator – annual growth rates.
- Real GDP – annual growth rates.
- Inflation – annual growth in CPI
- VIX - CBOE Market Volatility Index – levels
- Commodity Price Index: All Commodities (C001CXAP@IFS) – annual growth rates
- World: Energy Index (C001CXE@IFS) – annual growth rates
- World GDP (GDP for world, weighted by PPP) minus country GDP - annual growth rates

Table S5: Monetary and Fiscal Data description (with HAVER codes, where applicable)

Country	**Monetary instrument**	**Government spending**	**Tax**
US	Effective federal funds rate (FFED@USECON) Wu-Xia shadow rate (FFEDSHDW@USECON)	Government consumption nominal (GE@USNA) Government investment nominal (GI@USNA)	Government receipts nominal (GRCP@USNA) Government transfers nominal (GETFP@USNA) Government interest payments Nominal (GIPD@USNA)
Japan	Shadow Short Rate Point Estimates (N158RSSV@G10)	Government Final Consumption Expenditure, Value (Q158G@OUTLOOK)	Total Receipts, General Government Value (Q158GRF@OUTLOOK) Social Security Benefits Paid By General Government (Q158SSP@OUTLOOK) Social Security Benefits Paid By General Government (Q158SSP@OUTLOOK)
UK	Bank Rate (UNBEDR@UK) Wu-Xia shadow rate (UKSHDW@UK)	Government consumption nominal (NMRPQ@UK) Government investment nominal (RPZGQ@UK)	Total Receipts, General Government Value (ANBVQ@UK+ ANBWQ@UK) Social Security Benefits Paid By General Government (NMFXQ@UK+ GZSJQ@UK) Japan: Social Security Benefits Paid By General Government (NUGWQ@UK+GZSKQ@UK)
Euro area	Lemke et al. (2017) shadow rate	Government consumption nominal Government investment nominal	Government receipts nominal Government transfers nominal Government interest payments
Brazil	Interest Rate: Selic - Target Rate (N223RTAR@EMERGE, avg)	Government Consumption (S223NCGC@EMERGE)	Central Government Revenues: Assets Operations (N223FGR@EMERGE-N223FRAS@EMERGELA) Social Security Benefits (N223FEPS@EMERGELA)
China	Prime Lending Rate (N924FRRL@EMERGEPR) Money Supply: M2 (N924FM2@EMERGEPR)	Fixed Asset Investment funded by State Budgetary Funds (N924VUST@EMERGEPR)	Government Revenues CEIC code :4331701 (CFPAA)
India	RepoRate (N534RPV@EMERGEPR)	Central Govt expenditure (N534FGE@EMERGE)	Central Govt receipts (N534FGR@EMERGE)
Russia	Money Supply: M2 (H922FM2@EMERGECW)	Government Consumption Expenditure (H922NCGC@EMERGE)	Federal Budget Revenue (N922FGR@EMERGE)

Table S6: Marginal likelihood/ Deviance Information criteria for single country VAR. Models with higher marginal likelihood and smaller Deviance Information Criteria are preferred.

Lags	US	Jap	UK	EA	China	Brasil	India	Russia
Test	MLik/DIC	MLik/DIC	MLik/DIC	MLik/DIC	MLik/DIC	MLik/DIC	MLik/DIC	MLik/DIC
4	-145/1042	-223/926	-264/1129	-177/730	-299/1309	-316/1373	-376/1651	-405/1800
5	-239/1010	-219/907	-261/1113	-172/707	-294/1283	-311/1347	-370/1623	-398/1766
6	-235/992	-218.45/894	-257/1094	-170/699	-290/1265	-307/1325	-364/1598	-392/1738

Figure S23: Interest rate and inflation response to a 1% increase in government spending. Mean model results

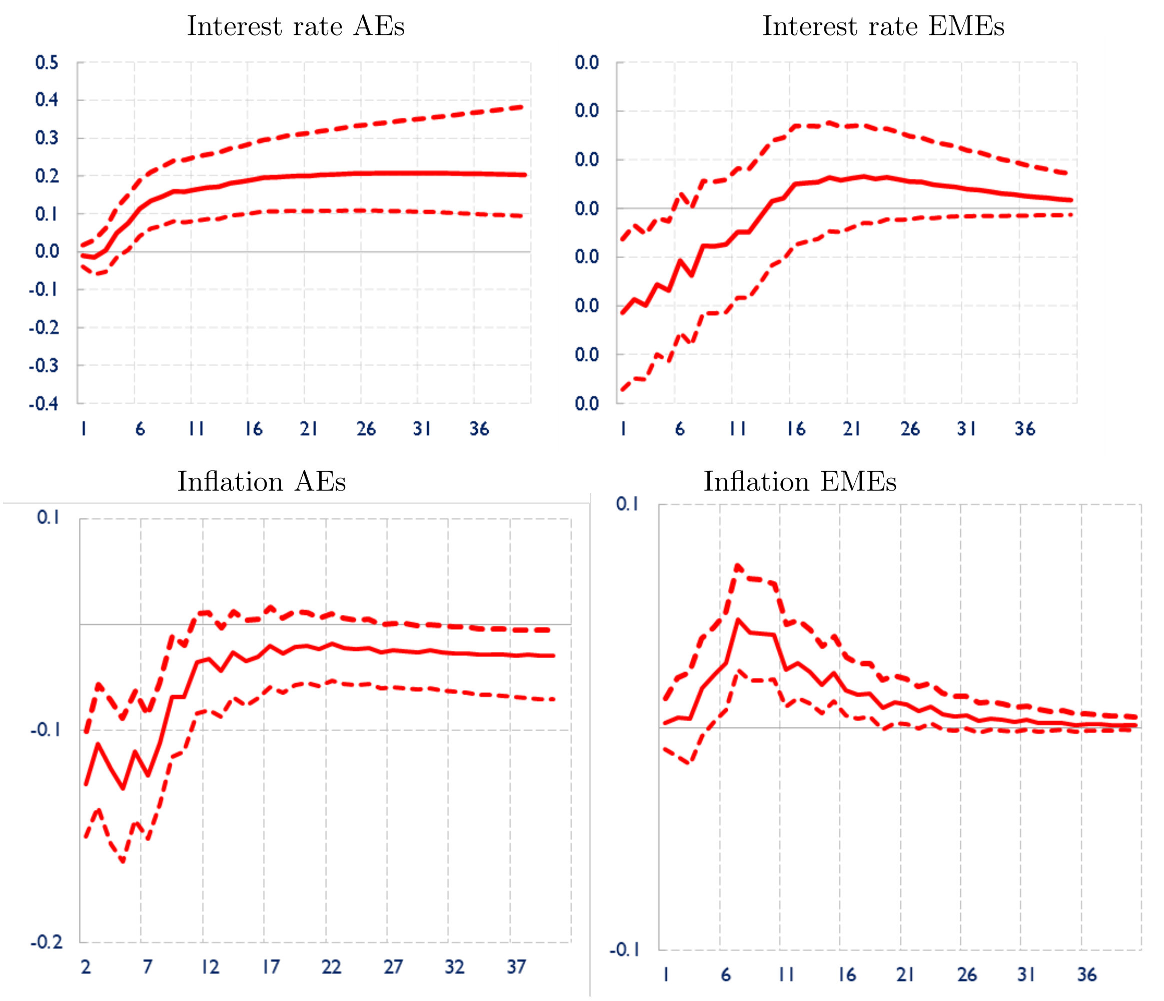


Figure S24: GDP response to fiscal and monetary shocks. Country results

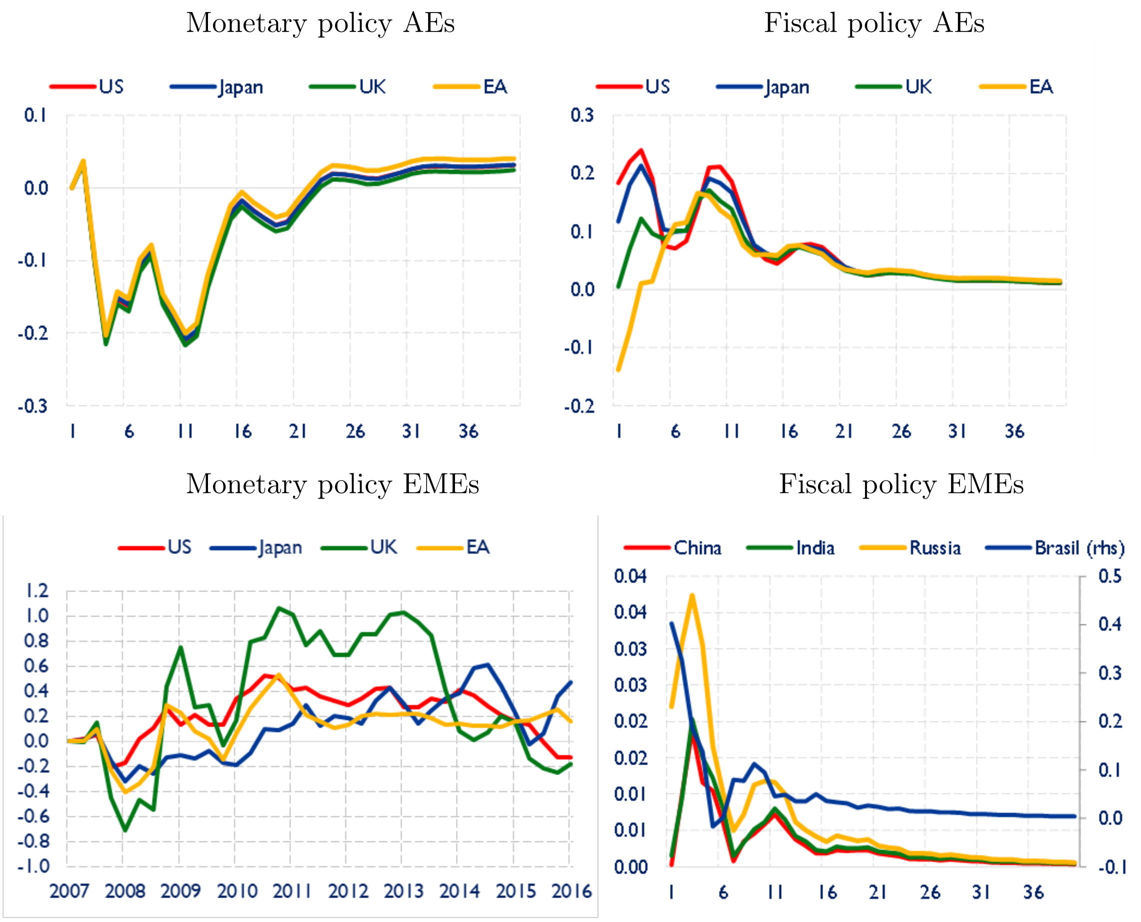


Figure S25: Sensitivity analysis to the prior on λ.

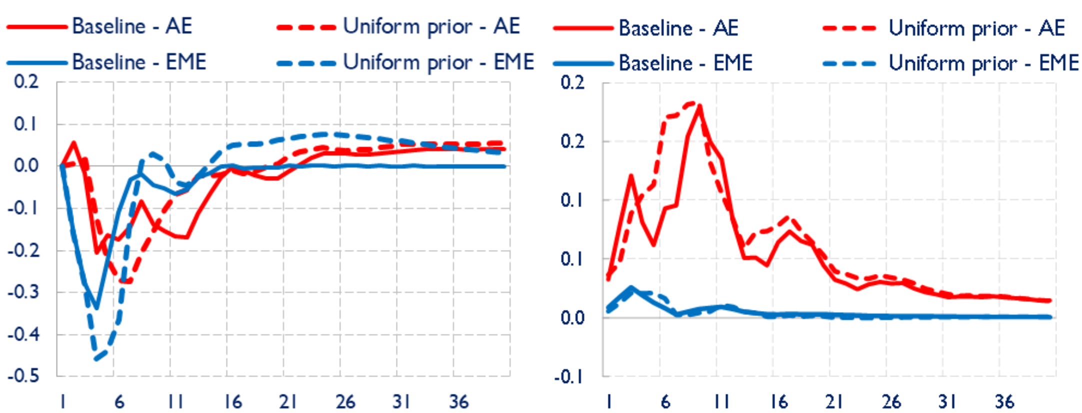


Figure S26: Sensitivity analysis to the number of lags for EMEs. Country results with 5 lags.

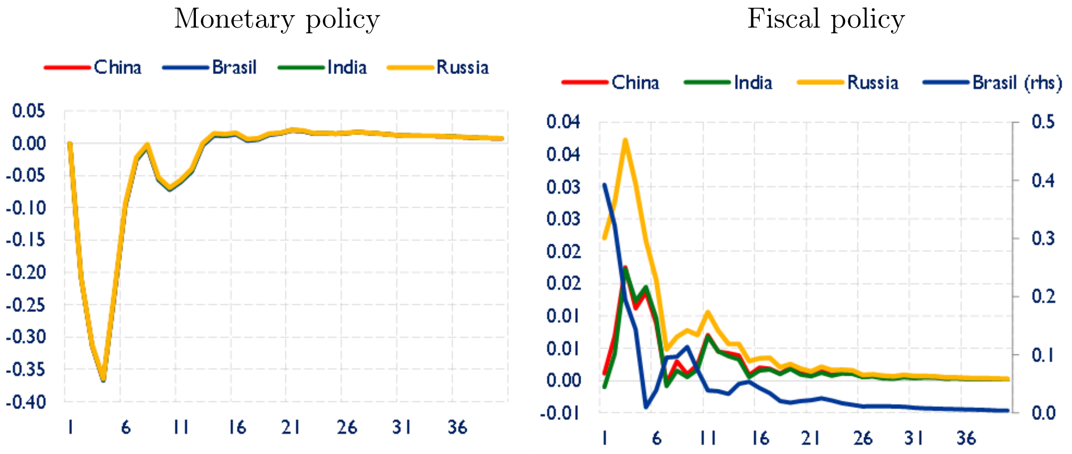


Figure S27: Monetary Policy Contribution in EMEs with M2 and R targeting

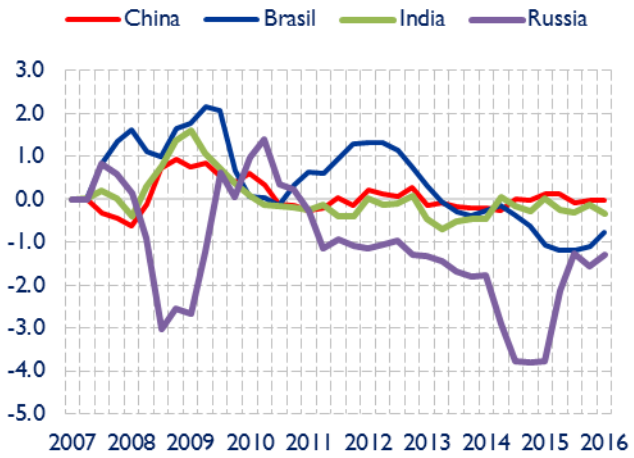


Figure S28: Sensitivity analysis to variables ordering for EMEs. Results with M2 ordered last.

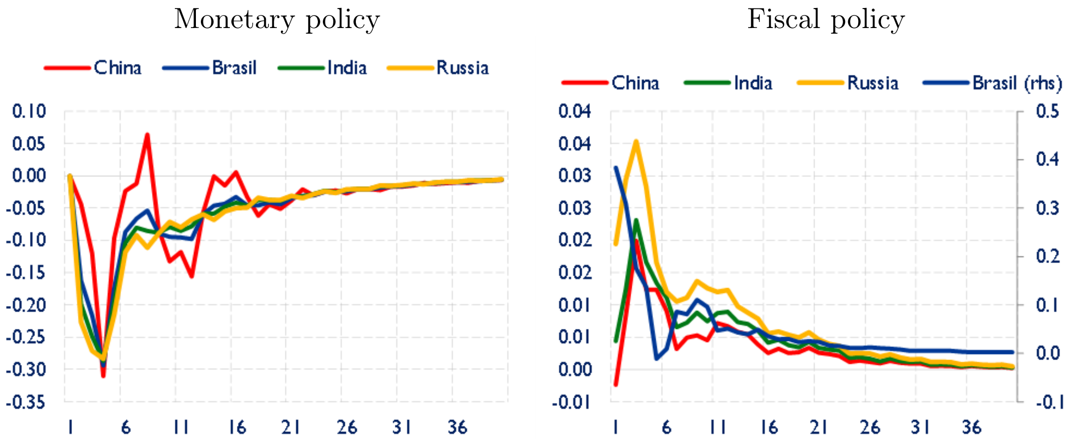


Figure S29: Sensitivity analysis to using Krippner shadow rate

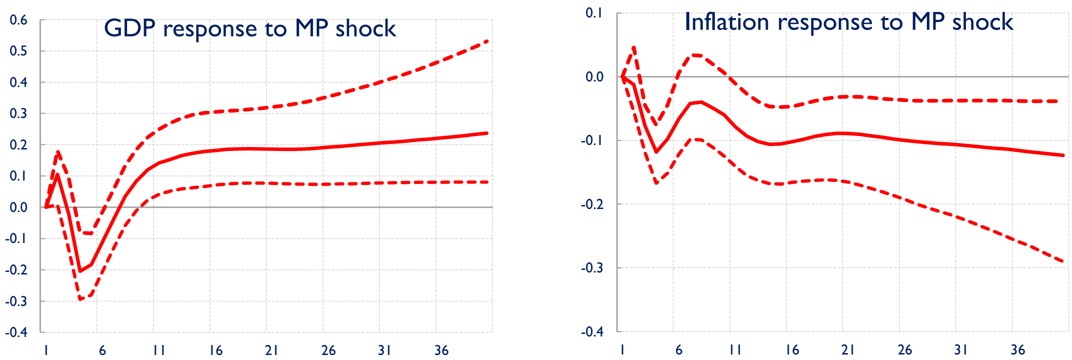


Figure S30: Conditional forecast AEs. Overall policy scenarios. Bands are 68 HPDI

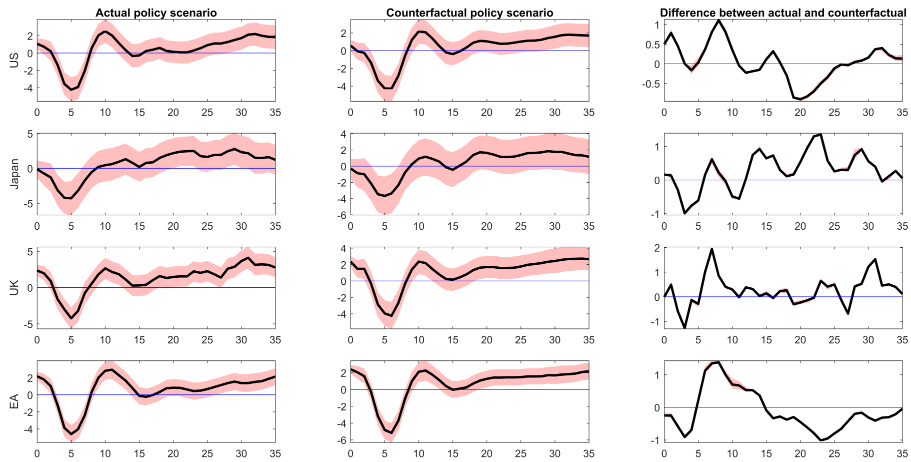


Figure S31: Conditional forecast EMEs. Overall policy scenarios. Bands are 68 HPDI

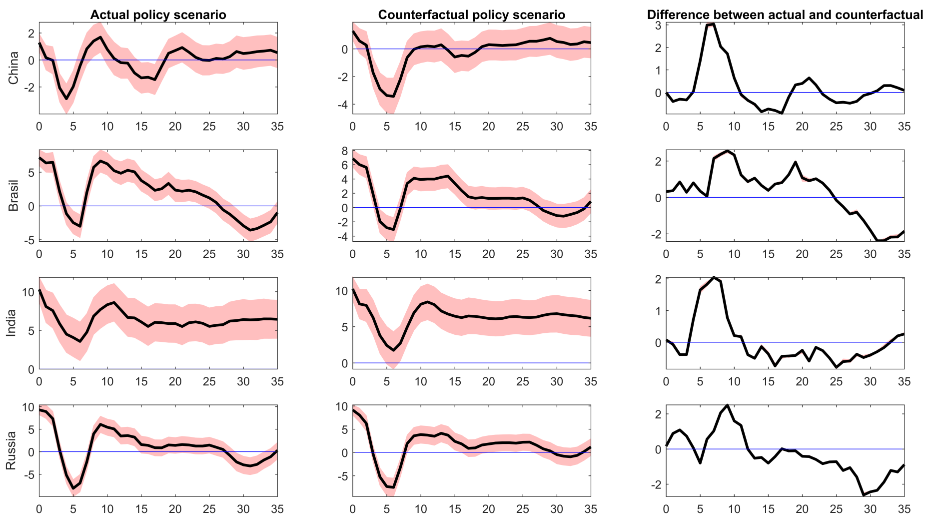
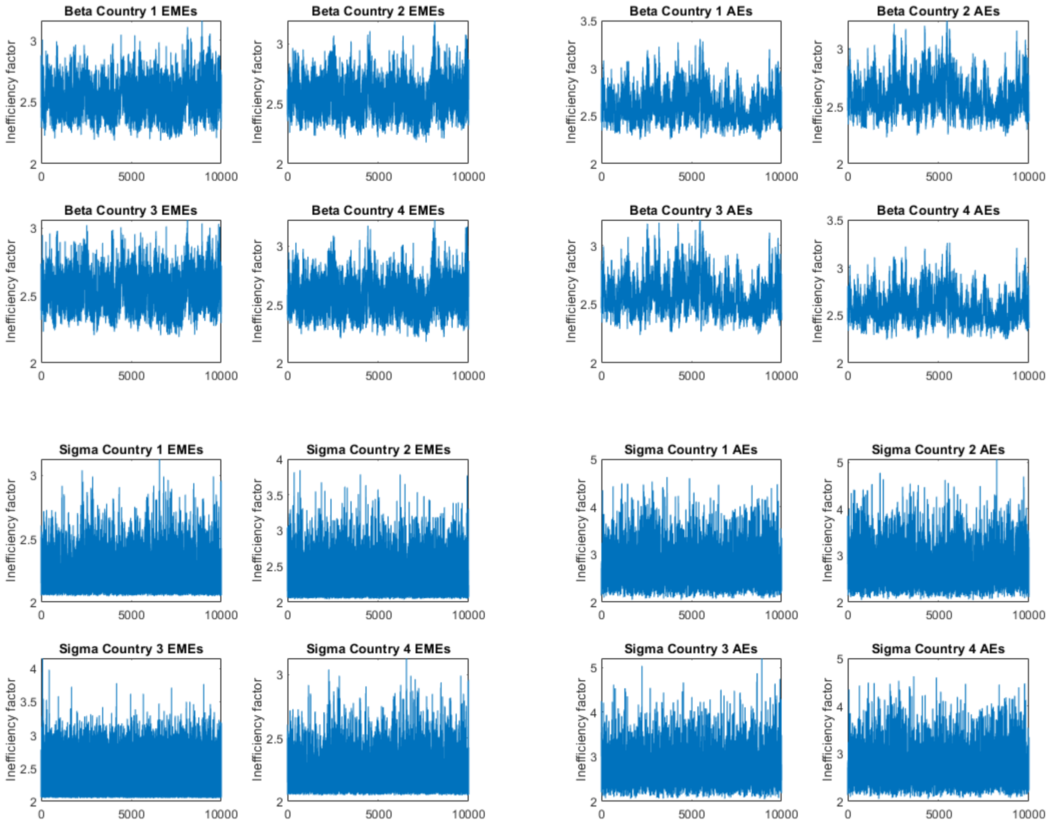


Figure S32: Inefficiency factors



Appendix Chapter 4

S1 Estimation

S1.1 Model

$$Y_{tc} = X_{tc}\beta_c + Z_t\theta_t + u_{tc} \tag{11}$$

$$u_{itc} = \gamma_{ic}M_t + \eta_{itc} \tag{12}$$

u_c ~ N(0,Σ) are the reduced form residuals for country c= 1,....,N, X_{tc} is the matrix of endogenous variables for country c while Z_t is a vector of exogenous variables common to all countries which enter the VAR equation at time t. For simplicity define $\Phi_c = \{\beta_c, \theta\}$ and $G_c = \{X_{tc}, Z_t\}$

η_{ic} ~ N(0,ω^2) are the residuals of the measurement equation. u_{itc} is the i^{th} residual where i= 1,.....n, represents the number of endogenous variables per country, M is the instrument for the structural shock of interest ε_i which is chosen to be the first for convenience.[7]

The reduced form shocks can be related to the underlying structural shocks as follows:

$$\varepsilon_{tc} = R_c u_{tc} \tag{13}$$

and we call ε_1 the shock of interest and ε_2 the remaining shocks. We aim at identifying the first column of matrix R for country c.

Instrument validity assumptions.

$E(\varepsilon_1 M) = \alpha$; $E(\varepsilon_2 M) = 0$

These are the relevance and exogeneity conditions for the instrument. Under these assumptions the first column of R is identified up to a scale as follows:

[7]Since we do not adopt a recursive identification the order of the variables has no implication for our object of interest (Impulse response functions).

$$R_{1c} = \begin{bmatrix} r_{11} \\ r_{21} \\ \vdots \\ r_{n1} \end{bmatrix} = s \begin{bmatrix} \gamma_{11} \\ \gamma_{21} \\ \vdots \\ \gamma_{n1} \end{bmatrix} \text{ where s is a scaling factor.}$$

For ease of exposition we split the parameters $\varTheta$ in two groups, the VAR parameters and the IV parameters :

$$\Theta_{VAR} = \left\{\Phi_c, \varSigma_c, \tau, \bar{\Phi}, \right\} \text{ and } \Theta_{IV} = \left\{\gamma_{1c}, \bar{\gamma}, \lambda, \omega_c^2, R\right\}.$$

Define the joint likelihood of the VAR data (G) and the instrument data (M):

$$P\left(G, M \mid \Theta\right) = P\left(G \mid \Theta_{VAR}\right) P\left(M \mid \Theta_{IV}, \Theta_{VAR}\right) \tag{14}$$

and combining the priors with (6) we re-write the posterior as in Rogers et al. (2016):

$$P\left(\Theta \mid D\right) = P\left(\Theta_{VAR} \mid G\right) P\left(\Theta_{IV} \mid \Theta_{VAR}, G\right) \tag{15}$$

where D contains both G and M.

The non closed form conditional posteriors are the $\varPhi$ and Σ while the rest of the parameters are standard with a known distribution to draw from.

S1.2 Priors

We assume a hierarchical prior for $\varPhi_c$ and γ_{ic} coefficients as below:

$$p\left(\Phi_c \mid \bar{\varPhi}, O_c, \tau\right) = N\left(\bar{\varPhi}, \tau O_c\right) \tag{16}$$

$$p\left(\gamma_{1c} \mid \bar{\gamma}, \Xi_c, \lambda\right) = N\left(\bar{\gamma}, \lambda \Xi_c\right) \tag{17}$$

where O_c is standard Minnesota prior and Ξ_c is an identity matrix.

We specify diffuse prior for $\bar{\varPhi}$, $\bar{\gamma}$,Σ and ω^2 :

$$p\left(\varSigma_c\right) \propto |\Sigma|^{-\frac{1}{2}(N+1)} \tag{18}$$

$$p(\omega_c^2) \propto \omega_c^2 \tag{19}$$

$$p(\bar{\varPhi}) \propto 1 \tag{20}$$

$$p\left(\bar{\gamma}\right) \propto 1 \tag{21}$$

and a uniform Inverse Gamma prior for τ and λ with s_0 and s_0^* = -1 and $v_0, v_0^* = 0$

$$p\left(\lambda\right) = IG\left(\frac{s_0^*}{2}, \frac{v_0^*}{2}\right) \tag{22}$$

$$p\left(\tau\right) = IG(\frac{s_0}{2}, \frac{v_0}{2}) \tag{23}$$

S1.3 Algorithm

1 Draw $P\left(\Phi_c^{new} \mid \Theta\right)$ and $P\left(\Sigma_c^{new} \mid \Theta, \Phi^{new}\right)$ using an Independence MH step use the proposal density for Φ and Σ with q(Φ) and q(Σ) defined as:

$$q(\Phi) = N(M, V) \quad with$$

$$M = V\left[\left(\left(\Sigma_c^{i-1}\right)^{-1}\right) Y_i + \left(\tau O_c\right)^{-1} \bar{\Phi}\right]$$

$$V = \left[\left(\Sigma_c^{i-1}\right)^{-1} \otimes G_c^{'} G_c + \left(\tau O_c\right)^{-1}\right]^{-1}$$

$$q(\Sigma) = IW(S_c, T_c) with$$

scale S_c= $\left(Y_c - G_c \Phi_c\right)^{'} \left(Y_c - G_c \Phi_c\right)$ and T_c degrees of freedom represented by the length of the time series. Notice that T is country specific.

Accept the proposal with probability:

$$\alpha = min\left(\frac{P(\Phi_c^{new}, \Sigma_c^{new}, \tau, \bar{\Phi}, \gamma_{1c}, \bar{\gamma}, \lambda, \omega_c)}{P(\Phi_c^{old}, \Sigma_c^{old}, \tau, \bar{\Phi}, \gamma_{1c}, \bar{\gamma}, \lambda, \omega_c)} \times q\frac{(\Phi_c^{old} \mid \Phi_c^{new})}{(\Phi_c^{new} \mid \Phi_c^{old})} \times q\frac{(\Sigma_c^{old} \mid \Sigma_c^{new})}{(\Sigma_c^{new} \mid \Sigma_c^{old})}, 1\right)$$

2. Draw γ_{ic} from $N(M^*, V^*)$ with:

$$M^* = V\left[\left(\left(\omega_c^2\right)^{-1}\right) u_i + \left(\lambda \Xi_c\right)^{-1} \bar{\gamma}\right]$$

$$V^* = \left[\left(\left(\omega_c^2\right)^{-1}\right) \times M_c^{'} M_c + \left(\lambda \Xi_c\right)^{-1}\right]^{-1}$$

3. Draw ω_c^2 from an inverse-Gamma distribution with scale parameter$(u_{ic} - M_c\gamma_{ic})^{'}(u_{ic} - M_c\gamma_{i}$
and T_c degrees of freedom for each i from 1 to n.

4. Draw R_{ic} from $N\left(\gamma_{ic}, \omega_c^2(M'M)^{-1}\right)$, for i=1...n;

Run Steps (1)-(4) for each country c=1....N

5. Draw $\bar{\varPhi}$ from $N(\Phi_m^c,\ N^{-1}\tau O_c)$ with $\Phi_m^c{=}N^{-1}\sum_{c=1}^{N}\Phi_c$

6. Draw $\bar{\gamma}$ from $N(\gamma_m^c,\ N^{-1}\lambda\Xi_c)$ with $\gamma_m^c{=}N^{-1}\sum_{c=1}^{N}\gamma_c$

7. Draw τ from an inverse Gamma distribution $(\frac{\bar{s}}{2}, \frac{\bar{v}}{2})$ with :

$\bar{s}{=}h + s_0$ where h is the number of VAR coefficients to be estimated for all units.

$$\bar{v} = v_0 + \sum_{c=1}^{N}\left\{\left(\Phi_c - \bar{\varPhi}\right)^{'}\left(\varSigma_c^{-1}\right)\left(\Phi_c - \bar{\varPhi}\right)\right\}$$

8. Draw λ from an inverse Gamma distribution $(\frac{\bar{s^*}}{2}, \frac{\bar{v^*}}{2})$ with

$\bar{s^*}{=}h^*{+}s_0^*$ where h^* is the number of IV coefficients to be estimated for all units.

$$\bar{v^*} = v_0^* + \sum_{c=1}^{N}\left\{\left(\gamma_c - \bar{\gamma}\right)^{'}\left(\omega_c^2\right)^{-1}\left(\gamma_c - \bar{\gamma}\right)\right\}$$

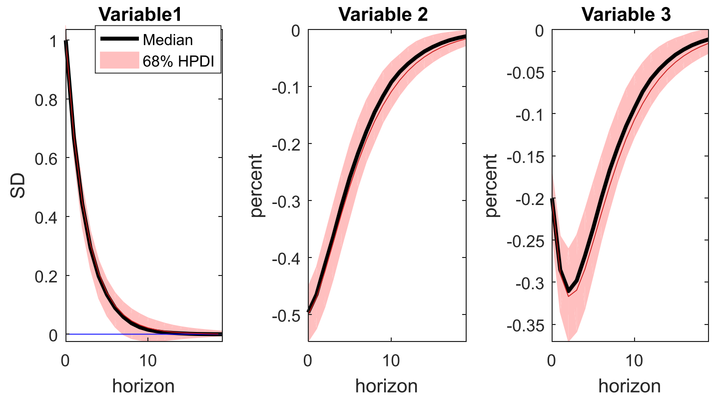
Steps 1-8 complete 1 draw.

S1.4 Monte-Carlo experiment

Artificial data is generated with the following characteristics: we generete 100 datasets. Each dataset contains data for 10 countries with 3 endogenous variables per country with the following coefficients:

$$\bar{\Phi} = \begin{bmatrix} 0.7 \\ 0.1 \\ -0.1 \\ -0.1 \\ 0.7 \\ 0.1 \\ -0.1 \\ 0.1 \\ 0.7 \end{bmatrix} ; \bar{\gamma} = \begin{bmatrix} 1 \\ -0.5 \\ -0.2 \end{bmatrix}$$

Figure S33: Monte-Carlo results. The red line is the true response. The black line is the median across the 100 datasets and the bands are 68 HPDI.



The sample length is set to 200 for each country and the first 100 observations are discarded to remove the influence of initial conditions. The model is estimated using 5000 iterations for each of the 100 datasets generated. The last 1000 observations are used for inference.

Figure S33 shows the comparison of the estimated and true impulse responses which suggests that the algorithm performs well.

S1.5 Convergence

We use 35,000 iterations in the benchmark estimation. We discard 20,000 draws and save 15000 for inference. The low values of the inefficiency factors reported in Figures S34 and S35 constitute evidence in favor of convergence.

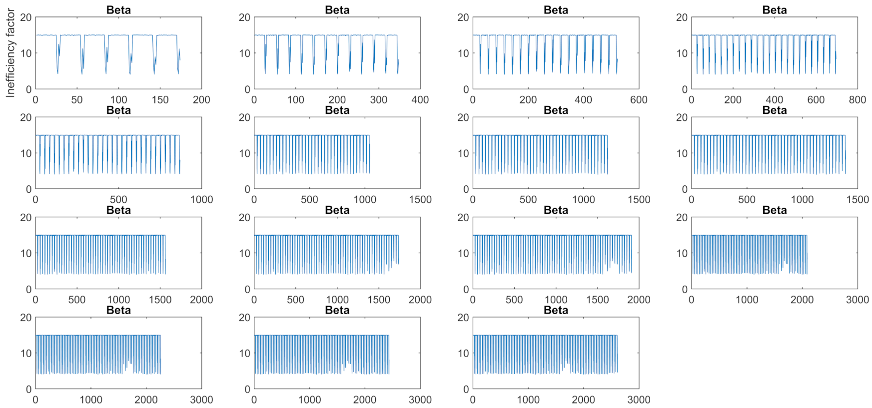
S1.6 DIC test

DIC is a goodness of fit statistic. It was introduced in Spiegelhalter et al. (2002) and is defined as:

$$DIC = \bar{D} + p_D$$

The first term is $\bar{D}$=E(-2lnL(Ψ_i))=$\frac{1}{M}\Sigma_i(-2lnL(\Psi_i)$ and L(Ψ_i) is the likelihood evaluated at the draws of all of the parameters Ψ_i in the MCMC chain. $\bar{D}$ is the posterior expectation of the deviation and it captures the fit of the model. The second term measures the model complexity and is defined as p_D=$\bar{D}$−D($\bar{\Psi}$). p_D can be approximated by $p_D = \frac{1}{M}\Sigma_i(-2lnL(\Psi_i))$-$\big(-2lnL(\frac{1}{M}\Sigma_i\Psi_i\big)$. Models with smaller DIC are preferred.

Figure S34: Inefficiency factors. VAR coefficients



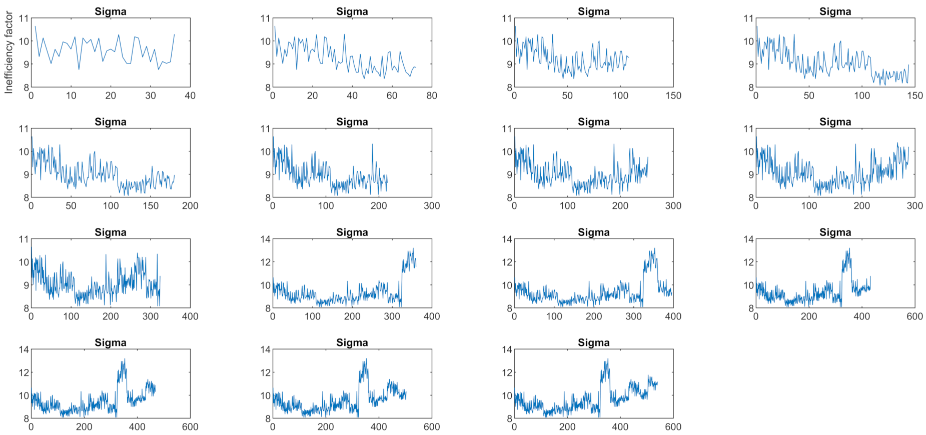


Figure S35: Inefficiency factors. IV coefficients

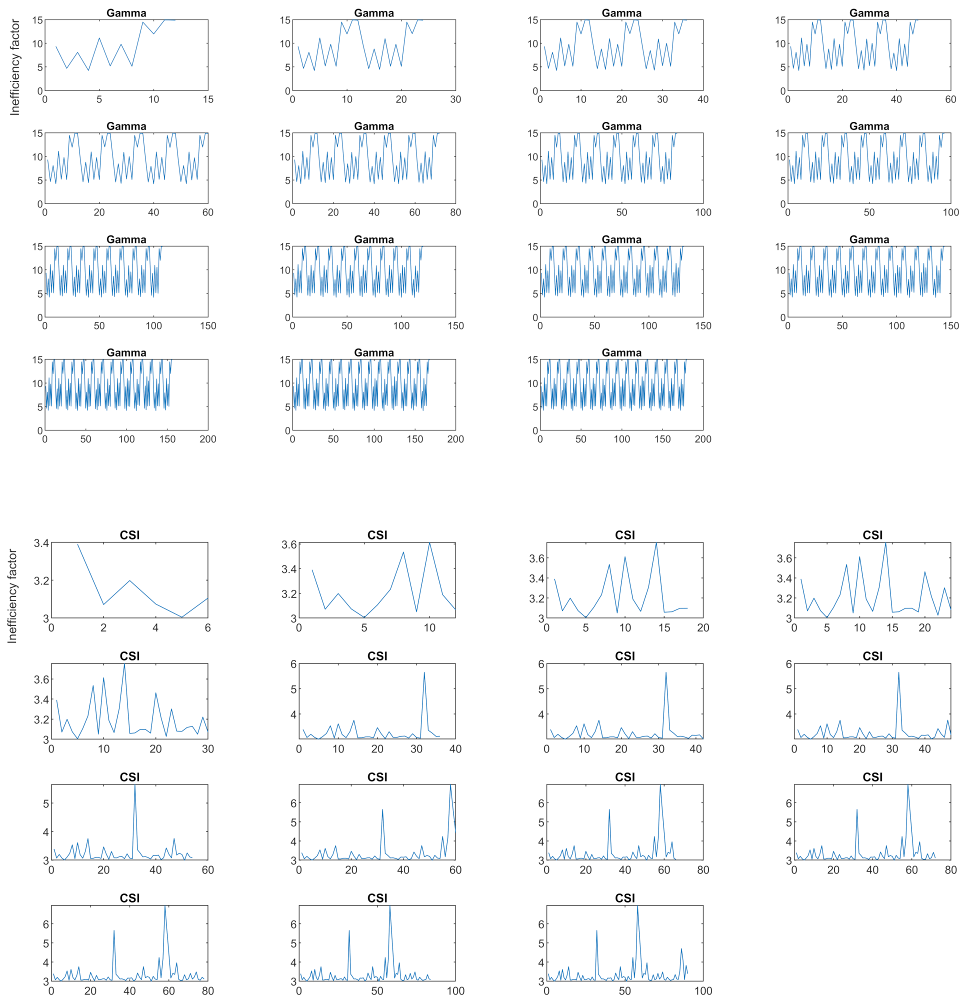


Table S7: Regression coefficients of the GDP residual on the instrument

Country	γ_{21}	95 HPDI	Country	γ_{21}	95 HPDI
1	-0.03	(-0.09 0.05)	9	-0.04	(-0.14 0.03)
2	-0.01	(-0.07 0.07)	10	-0.03	(-0.12 0.05)
3	-0.03	(-0.11 0.04)	11	-0.05	(-0.15 0.03)
4	-0.03	(-0.11 0.05)	12	-0.02	(-0.09 0.07)
5	-0.03	(-0.10 0.05)	13	-0.02	(-0.09 0.08)
6	-0.04	(-0.11 0.04)	14	-0.03	(-0.12 0.05)
7	-0.03	(-0.11 0.05)	15	-0.04	(-0.14 0.03)
8	-0.03	(-0.11 0.04)			

S2 Sensitivity analysis and additional results

In this section we report the results of the robustness checks performed. Specifically, Table S8 reports the ranking of the regressors obtained using Spike and Slab algorithm for variable selection. If we were to apply a rule of using regressors with a relevance higher than 0.40 it would deliver almost the same specifications as in the benchmark case.

Figures S37 and S38 show the impulse responses for the average country obtained using VIX and EPU as instrument for the uncertainty shock. In Figures S39-S41 we report the impulse responses achieved using alternative specifications for the world demand proxy and for the trend variables specification.

Additionally in Figures S42 and S43 we report median impulse responses and variance decomposition across countries for all the variables in the model.

Finally, table S7 reports the regression coefficients of the GDP residual on the instrument.

Table S8: Spike and Slab algorithm raking of regressors. Median of relevance parameter in bracket

Variable	IRF	Variance decomposition
Trade	1 (0.67)	6 (0.50)
GDP pc	2 (0.57)	8 (0.43)
Dolarisation	3 (0.49)	7 (0.49)
Manufacturing	4 (0.46)	1 (0.63)
Goods mkt efficincy	5 (0.45)	2 (0.59)
Labor mkt mfficiency	6 (0.38)	4 (0.55)
Product diversification	7 (0.38)	3 (0.56)
Domestic credit	8 (0.37)	5 (0.53)
Product concerntration	9 (0.37)	9 (0.42)

Figure S36: Cholesky vs proxy identification. Uncertainty ordered first.

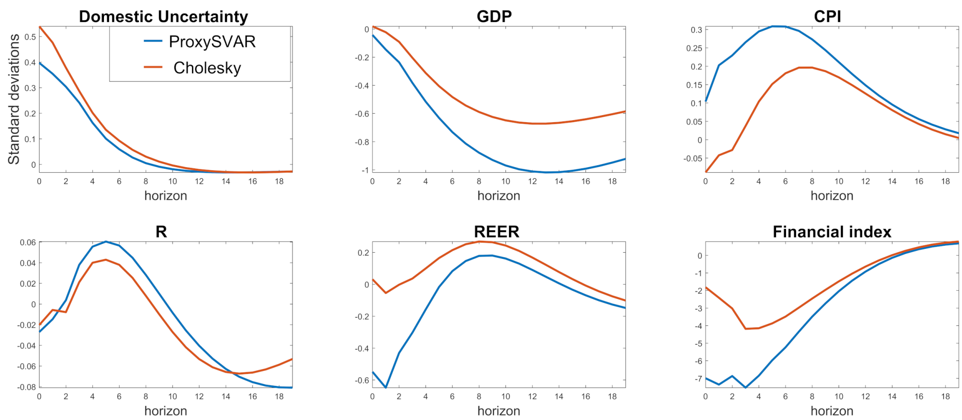


Figure S37: Average country impulse responses. VIX used as proxy

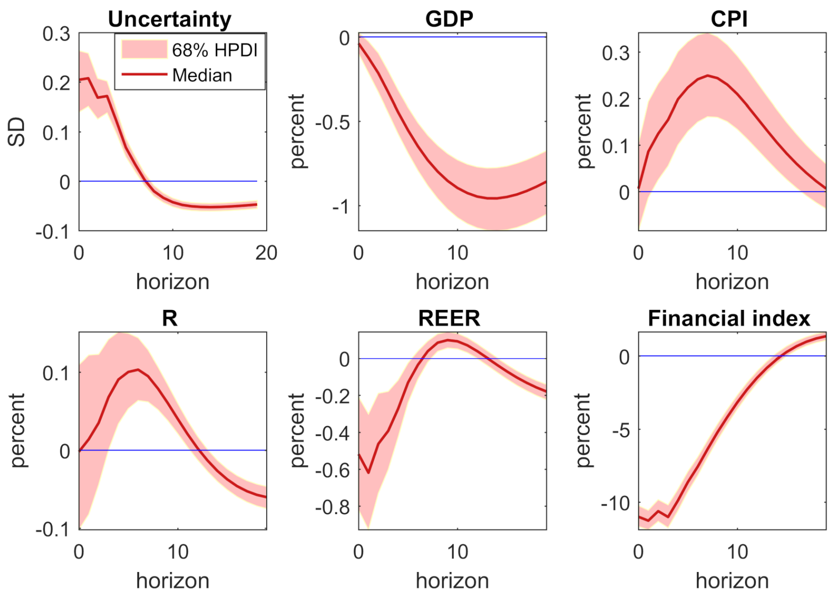


Figure S38: Average country impulse responses. EPU used as proxy

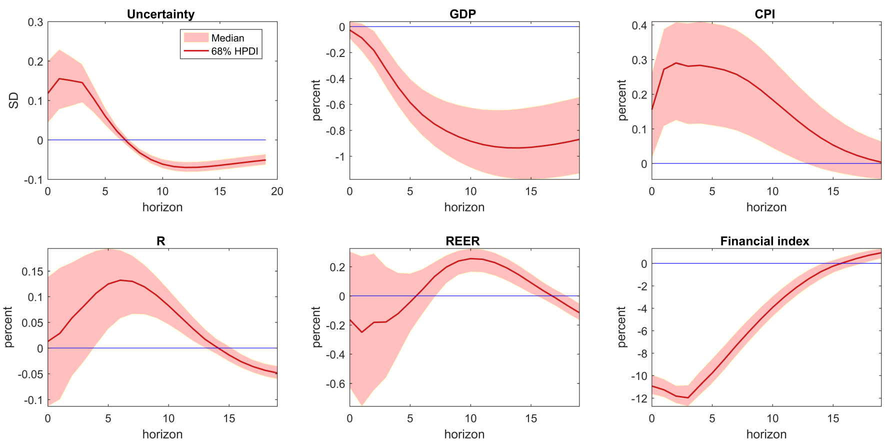


Figure S39: Average country impulse responses. World demand proxied by Kilian index

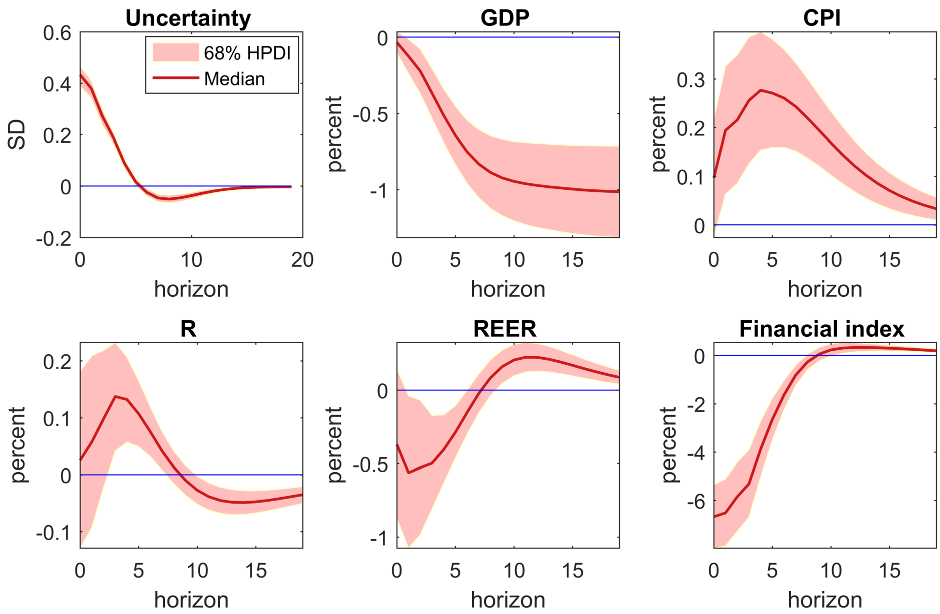


Figure S40: Average country impulse responses. No linear trend

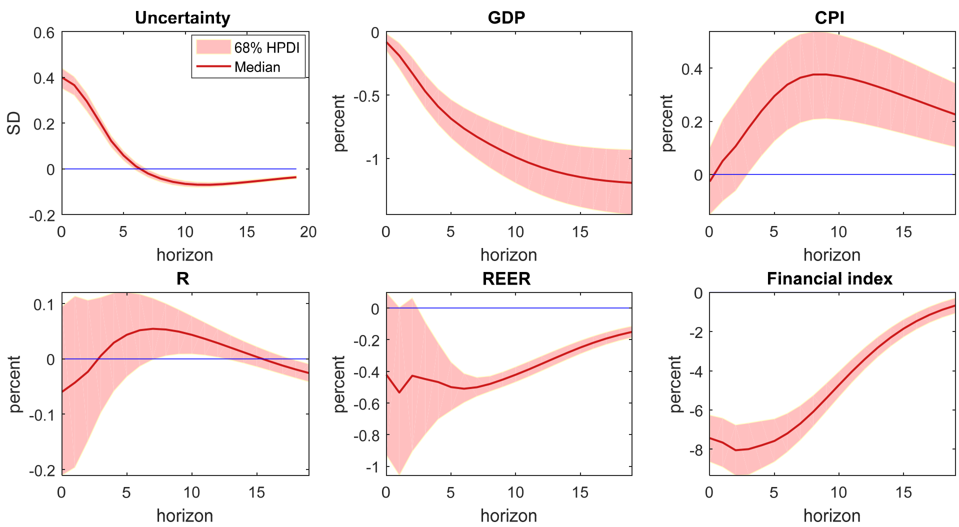


Figure S41: Average country impulse responses. Linear and quadratic trend

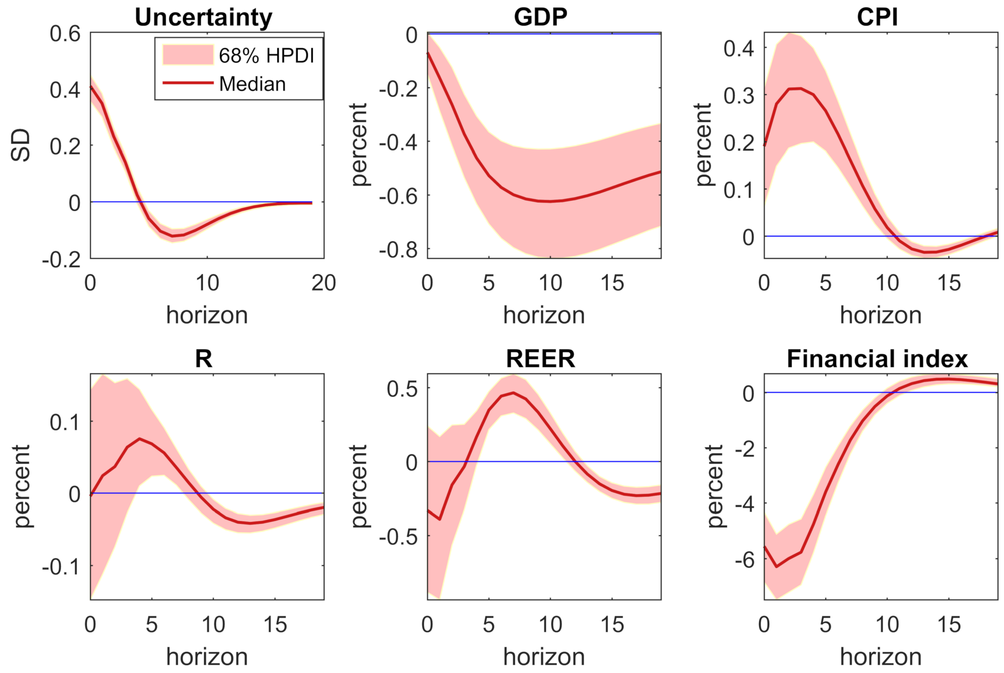


Figure S42: Impulse responses. Posterior median estimate for each country. The shock is scaled to increase the domestic uncertainty by 1 unit.

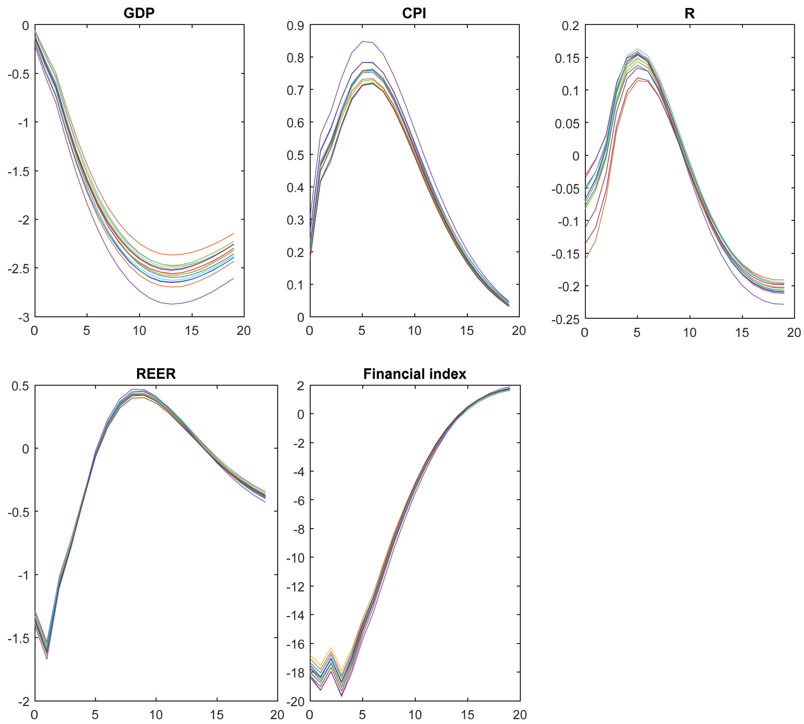
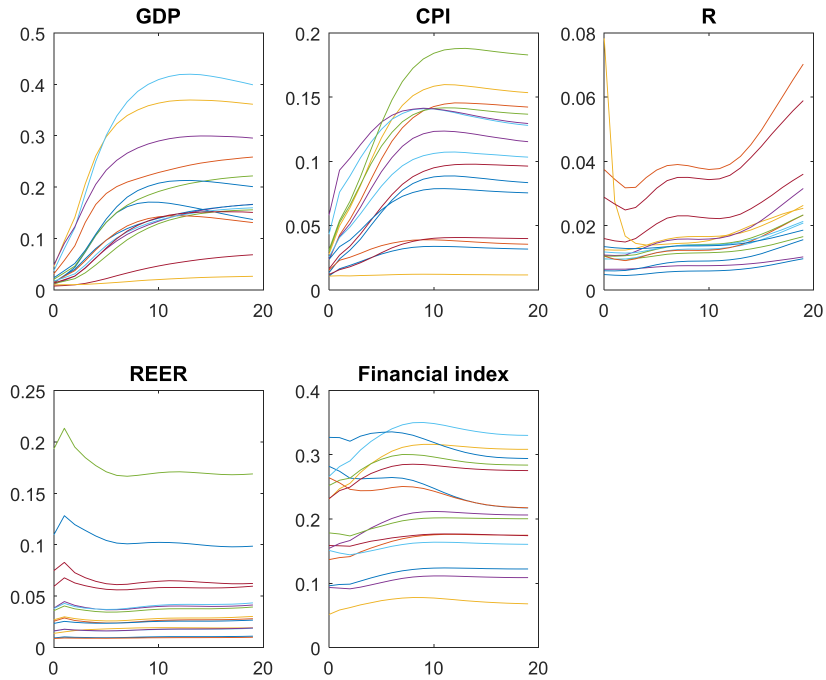


Figure S43: Variance decomposition. Posterior median estimate for each country.



S3 Data description

In this section we describe the data used in the empirical exercise.

Mumtaz and Musso (2018) OECD dataset

	Countries		Series	Definition	Sources
1	Germany	1	REAL GDP	REAL GDP	OECD
2	France	2	CPI	CONSUMER PRICE INDEX	OECD
3	Italy	3	STI	SHORT-TERM INTEREST RATE	BIS, IMF, OECD
4	Spain	4	STP	STOCK PRICES	BIS, IMF, OECD
5	Netherlands	5	CREDIT	CREDIT TO THE PRIVATE SECTOR	BIS, IMF, OECD
6	Belgium	6	LOANS	BANK LOANS TO THE PRIVATE SECTOR	BIS, IMF, OECD
7	Austria	7	HOUSEP	HOUSE PRICES	BIS, IMF, OECD
8	Finland	8	BROADM	BROAD MONEY	ECB, BIS, IMF, OECD
9	Greece	9	NARROWM	NARROW MONEY	ECB, BIS, IMF, OECD
10	Ireland	10	INDPROD	INDUSTRIAL PRODUCTION	IMF, OECD
11	Portugal	11	RETSALES	RETAIL SALES VOLUMES	OECD, FED (FRED II)
12	United States	12	EMPL	EMPLOYMENT	BIS, OECD
13	United Kingdom	13	UR	UNEMPLOYMENT RATE	OECD, EC (AMECO interp)
14	Japan	14	RGFCF	REAL GROSS FIXED CAPITAL FORMATION	OECD, BIS, EC (AMECO interp)
15	Canada	15	RPCON	REAL PRIVATE CONSUMPTION	OECD, BIS, EC (AMECO interp)
16	Australia	16	REXP	REAL EXPORTS	OECD, BIS, EC (AMECO interp)
17	South Korea	17	RIMP	REAL IMPORTS	OECD, BIS, EC (AMECO interp)
18	Nez Zealand	18	NEER	NOMINAL EFFECTIVE EXCHANGE RATE	IMF, OECD
19	Norway	19	USDX	US DOLLAR EXCHANGE RATE	IMF, OECD
20	Sweden	20	LTI	LONG-TERM INTEREST RATE	BIS, IMF, OECD
21	Switzerland	21-28	WORLD	INTERNATIONAL COMMODITY PRICES	WORLD BANK
22	Denmark	29-40	WORLD	EMERGING ECONOMIES INDICATORS	IMF, OECD

23 Specific international commodity prices (8)

12 emerging market economies indicators

(5 for South Africa, 4 for Mexico and 1 each for China, India and Turkey).

Cross section analysis data

Indicator Name	Source
Domestic credit to private sector (% of GDP)	World Bank
GDP per capita, PPP (constant 2011 international $)	World Bank
Trade (% of GDP)	World Bank
Manufacturing, value added (% of GDP)	World Bank
Dollarization index	Levy Yeyati website
Labour market flexibility	World Economic Forum Competitiveness Database- Pillar 7
Product market flexibility	World Economic Forum Competitiveness Database- Pillar 6
Herfindahl-Hirschman index	UNCTAD

EMEs data description

Argentina	Chile
RGDP	RGDP
CPI	Consumer Price Index, All items
Deposit rate	Central Bank Minimum Interest Rate
REER	REER
Buenos Aires SE General Index (IVBNG)	Santiago SE Indice General de Precios de Acciones
Total Reserves excluding Gold	Total Reserves excluding Gold
Official Reserve Assets, US Dollars	Official Reserve Assets, US Dollars
Currency in Circulation	National Currency per U.S. Dollar
Export of Goods	Currency in Circulation
M1	Export of Goods
M3	Imports of Goods
Imports of Goods	Industrial Production Volume SA
2003q4 to 2016q2	M1
	Unemployment Rate
	1997q2 to 2016q4

Colombia	Croatia
RGDP	RGDP
Consumer Price Index, All items	Consumer Price Index, All items
Bank of the Republic Intervention Rate	Bank of Croatia Discount Rate
REER	REER
IGBC General Index	Bourse Index (CROBEX)
Total Reserves excluding Gold	Total Reserves excluding Gold
Official Reserve Assets, US Dollars	Official Reserve Assets, US Dollars
National Currency per US Dollar	National Currency per US Dollar
Export of Goods	Cental Bank Overnight Credit
Imports of Goods	Imports of Goods
Industrial Production Volume SA	Croatia Exports of Goods
Unemployment Rate	**2001q4 to 2016q4**
M1	
M2	
M3	
Currency in Circulation	
2000q2 to 2016q4	

Czech rep	Hungary
RGDP	RGDP
Consumer Price Index, All items	Consumer Price Index, All items
Central Bank Deposit Facility	Bank of Base Rate
REER	REER
Prague SE PX Index	Vienna OETEB Traded Index (Forint)
Final Consumption Expenditure, Private	Final Consumption Expenditure, Private
Final Consumption Expenditure, Public	Final Consumption Expenditure, Public
Gross Capital Formation	Gross Capital Formation
Total Reserves excluding Gold	Total Reserves excluding Gold
Official Reserve Assets, US Dollars	Official Reserve Assets, US Dollars
Unemployment Percentage change previous year	Unemployment Percentage change period previous year
Unemployment, Percentage change, previous period	Unemployment, Percentage change, previous period
National Bank 2 Week Repo Rate	Export of Goods
Export of Goods	Imports of Goods
Imports of Goods	**1997q2 to 2016q4**
Industrial Production Volume SA	
1997q2 to 2016q4	

Peru	Philippines
RGDP	RGDP
Consumer Price Index, All items	Consumer Price Index, All items
Central Bank of Peru Discount Rate	Philippines Central Bank Discount Rate
REER	REER
Lima S&P/BVL Peru General Index	Manila SE Composite Index

Total Reserves excluding Gold
Official Reserve Assets, US Dollars
National Currency per US Dollar
Export of Goods
Imports of Goods
Industrial Production Volume SA
1997q2 to 2016q4

Total Reserves excluding Gold
Official Reserve Assets, US Dollars
Consumer Price Index Inflation Rate
Export of Goods
Imports of Goods
Industrial Production Volume SA
Unemployment Rate
1997q2 to 2016q4

Poland

RGDP
Consumer Price Index, All items
Bank of Poland Lombard Rate
REER
Warsaw SE 20-Share Composite
Final Consumption Expenditure, Private
Final Consumption Expenditure, Public
Gross Capital Formation
Total Reserves excluding Gold
Official Reserve Assets, US Dollars
Central Bank Refinancing Rate
Export of Goods
Imports of Goods
Industrial Production Volume SA
1997q2 to 2016q4

Romania

RGDP
Consumer Price Index, All items
Romania NRC Structural Credit Rate
REER
Bucharest SE Index in Lei
Financial, Interest Rates, Money Market, Percent per annum
Final Consumption Expenditure, Private
Final Consumption Expenditure, Public
Gross Capital Formation
Total Reserves excluding Gold
Official Reserve Assets, US Dollars
Unemployment Percentage change, period previous year
Unemployment, Percentage change, previous period
Currency in Circulation
Export of Goods
Imports of Goods
Industrial Production Volume SA
2001q2 to 2016q2

Singapore

RGDP
Consumer Price Index, All items
Repo rate
REER
Dow Jones Singapore Stock Index USD
Imports of Goods
Total Reserves excluding Gold
Official Reserve Assets, US Dollars
National Currency per US Dollar
Export of Goods
FTSE Straits-Times Index
Industrial Production Volume SA
1997q2 to 2016q4

Slovenia

RGDP
Consumer Price Index, All items
Financial, Interest Rates, Lending Rate, Percent per annum
REER
SE SBITOP Blue Chip Index
Final Consumption Expenditure, Private
Final Consumption Expenditure, Private
Final Consumption Expenditure, Public
Final Consumption Expenditure, Public
Gross Capital Formation, Changes in Inventories, Nominal
Currency in Circulation
Export of Goods
Imports of Goods
Industrial Production Volume SA
1997q2 to 2016q4

South Africa

RGDP
Consumer Price Index, All items
Central bank Interest rate
REER
FTSE/JSE Finance and Industrials Top 30
Official Reserve Assets, US Dollars
National Currency per US Dollar
FTSE/JSE Top 40 Tradeable Stocks
Export of Goods
Imports of Goods
Industrial Production Volume SA
Currency in Circulation
M1
M2
1997q2 to 2016q4

Thailand

RGDP
Consumer Price Index Inflation Rate
Bank of Thailand Lending Facility Rate
REER
SET General Index
Currency in Circulation
Export of Goods
Imports of Goods
Industrial Production Volume SA
M1
2001q4 to 2016q4

Turkey
RGDP
Consumer Price Index, All items
Turkey Central Bank Lending Rate
REER
Istanbul SE IMKB-100 Price Index
Final Consumption Expenditure, Private
Final Consumption Expenditure, Public
Gross Capital Formation
Total Reserves excluding Gold
Official Reserve Assets, US Dollars
Central Bank Discount Rate
Currency in Circulation
Export of Goods
Imports of Goods
Industrial Production Volume SA
2004q2 to 2016q4

Data sources: IMF, Global Financial Data, BIS and country specific central bank websites for policy rates.

Appendix A

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